

FUTURE MEGAFIRES AND SMOKE IMPACTS

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ABSTRACT

“Megafire” events, in which large high-intensity fires propagate over extended periods, can cause both immense damage to the local environment and catastrophic air quality impacts on cities and towns downwind. Increases in extreme events associated with climate change (e.g., droughts, heat waves) are projected to result in more frequent and extensive very large fires exhibiting extreme fire behavior (*IPCC, 2007; Flannigan et al., 2009*), especially when combined with fuel accumulation resulting from past fire suppression practices and an expanding wildland-urban interface. Maintaining current levels of fire suppression effectiveness is already proving challenging under these conditions, making more megafires a strong future possibility.

This project examines the weather and climate factors related to known megafires and very large wildfires that have occurred across the contiguous United States and projects the likelihood of megafires occurring during the 2046-2065 mid-century time period. A variety of statistical techniques and spatial scales are used in the analysis. The report ranks regions of future higher likelihood very large fire locations based on overall probability. In addition, the potential for large-scale smoke impact effects from very large fires is examined. This includes the overall potential for smoke emissions, as well as the potential for downwind transport to various kinds of sensitive receptors. Types of sensitive receptors examined include Class 1 airsheds, National Ambient Air Quality Standards non-attainment areas, and overall human population exposure. Smoke emissions and downwind transportation are combined to create an overall metric of Smoke Impact Potential (SIP). Combining future very large fire projections with site specific Smoke Impact Potentials allows for the ranking of locations based on the potential for large scale smoke impacts from very large fires.

While overall megafire risk is high in many parts of the western U.S. as well as in more limited areas along the east coast and the upper Midwest, the potential human population exposure from megafires is heavily concentrated in California, Minnesota, and along the eastern seaboard. A complete ranking of these locations is provided in the report.

1. INTRODUCTION

This project was designed to examine changes in the occurrence of megafires and their potential smoke impacts on population centers under climate change scenarios. Observed increases in the occurrence of very large wildfire, or ‘megafires,’ in recent decades have increased concerns of widespread air quality impacts. Identifying those areas where megafires are likely to occur in the future and prioritizing these areas based on their potential air quality impacts can help prioritize management actions that may be able to mitigate megafire risk and impact.

Background

“Megafire” events, in which large high-intensity fires propagate over extended periods, can cause both immense damage to the local environment and catastrophic air-quality impacts on cities and towns downwind. The extensive 2010 fires in western Russia are perhaps the best example of megafires’ potential to impact air quality, as widespread and prolonged smoke pollution exposed millions to unhealthy air. Increases in extreme events associated with climate change (e.g., droughts, heat waves) are projected to result in more frequent and extensive very large fires exhibiting extreme fire behavior (IPCC, 2007; Flannigan et al., 2009), especially when combined with fuel accumulation resulting from past fire exclusion and an expanding wildland-urban interface. There is a pressing need both to identify future potential megafire situations and to understand their full impact on the environment, including implications for air quality. Future fire-management strategies will also be complicated by recent and expected stricter air quality standards on particulate matter, ozone, and regional haze, all of which are exacerbated by smoke, and non-fire emissions from demographic, land-use, and other sector changes that contribute to increased “background” pollution.

Known issues – defining megafire

While no strict objective definition of “megafire” has been agreed upon – indeed, studies of megafire (e.g., Brookings, 2005) have pointed to the socio-political aspects of what is labeled a “megafire” – megafires are commonly understood to be very large, intense, and uncontrollable fires. Some have displayed highly energetic fire behavior (e.g., the 2009 “Black Saturday” fires in Australia), while others have had prodigious prolonged fuel consumption (e.g., the 2007 Okefenokee Swamp fires). Regardless of the particular label, there is a clear need to understand and predict periods when such very large and prolonged fires can develop in a way that is not responsive to standard suppression, and to quantify their impacts on cities and towns downwind. For this reason, in the report, we use the generic term “megafire” to mean not just known, named megafires, but also the very largest fires (identified as the largest 0.5-5 % of fires by size) and we refer to identified megafires (e.g., in Brookings, 2005) as “named megafires.”

Project objectives

The major project objectives were to:

- Identify the likely locations and timings of future megafires;
- Analyze the ability of smoke from these potential megafires to reach cities and other sensitive receptors.

Secondary goals were to create probabilistic models of megafires from fire-climate and fire-weather relationships and apply these models to climate scenarios to project megafires for the mid-21st century; quantify the smoke impacts from these megafires on cities; and assess how these smoke plumes might affect regional haze and other visibility concerns.

Project outline and progress

The project focused on a sequence of questions:

- What is a megafire?
- When and where have megafires occurred?
- What are the commonalities and differences in factors that contribute to their occurrence?
- How can we predict megafire occurrence probabilities from weather, climate, ecosystem type, and other information?
- Where are megafires most likely to occur in the future?
- What are the likely smoke impacts from these projected megafires?
- What are the implications in terms of visibility, the National Ambient Air Quality Standards, etc.?
- How can we rank the locations where megafires are likely to occur?
- How does this ranking change when we consider the smoke implications?

To address these, the project undertook a sequence of linked steps:

- Examined the commonalities and differences in megafires;
- Decided on an objective definition of megafires;
- Created a statistical model of megafire occurrence;
- Projected future megafire probabilities under future climate scenarios;
- Given future megafire probabilities, projected future megafire emissions;
- Examined where the projected megafire smoke emissions will likely go;
- Examined the impact of projected megafire smoke on populations;
- Examined the impact of projected megafire smoke on visibility and other air quality concerns;
- Ranked the locations most at risk for future megafires; and
- Refined these rankings based on potential smoke impacts.

2. STUDY DESIGN

After the study initially defined megafires and found commonalities in megafires, the Study Design encompassed two analytical tracks: (i) creating statistical models of megafire probability and using these models with climate projections to model future megafire probability, and (ii) analyzing the smoke impacts of future megafires. Several successive statistical models of megafire probabilities were created – one at a regional (GACC) scale, one at an ecoregion scale, one at a Predictive Service Area scale, and one at a ~60km grid scale. A large-scale synthesis effort examined the many different approaches, focusing on the best methodologies and results described here.

Overview

This work primarily relies on synthesizing existing datasets and model output, supplemented with focused modeling to support conclusions or fill information gaps. Many models and datasets used to analyze the potential smoke impacts from megafires were previously developed in other projects or available through outside sources, as were the weather, climate, and fire indices used to identify potential future megafire locations.

Study area / scope

- **Space:** CONUS (lower 48 states).
- **Time:** Historical period: 1984-2012.
Future period: 2041-2070.
- **Fire size:** Fires ≥ 1000 acres.

Datasets

There are several datasets used in this work:

Fire occurrence and size:

We use *fire occurrence* from the Monitoring Trends in Burn Severity (MTBS) database for the period 1984-2012. MTBS records all fires greater than 1000 acres in the western U.S. and all fires greater than 500 acres in the eastern U.S. Some fires smaller than this are also recorded in MTBS, but we filter out all fires < 1000 acres of final fire size here. We also determine *final fire size* from only the portion of the MTBS perimeter categorized as burned (eliminating ‘unburned to low’ category). This can significantly reduce the final fire size as compared what would be estimated using only the fire perimeter (Kolden et al., 2012). Data available at:

- <http://www.mtbs.gov/>

Historical weather:

We use 4-km daily gridded weather data for 1979-2012 produced from daily surface meteorological data of Abatzoglou (2013). Data available at:

- <http://metdata.northwestknowledge.net/>

Future weather and climate:

We use 4-km daily gridded daily weather for 1950-2099 time periods produced through downscaling of global climate model data using the Multivariate Adaptive Constructed Analogs method (Abatzoglou and Brown, 2012). A total of 17 global climate models (GCM) were downscaled for both historical (1950-2005) and future (2006-2099) simulations using Representative Concentration Pathway 4.5 (RCP4.5) and 8.5 (RCP8.5) for the period 1950-2005 and Representative Concentration Pathway 8.5 for 2006-2099. Data available at:

- <http://maca.northwestknowledge.net>

Trajectory climatology:

We utilize a cached set of 600 Million+ forward trajectories done as part of JFSP Project #10-S-02-1 (PI: Larkin). These trajectories were created by performing forward HYSPLIT trajectory runs every 6 hours for a 30-year period (1979-2009) across CONUS and are available through JFSP Project #10-S-02-1 (11Terrabytes).

Gridded historical weather data for smoke dispersion:

For smoke-dispersion modeling, fully evolving gridded 4-dimensional (x,y,z,t) weather data are required. We use the modeled output from the North American Regional Reanalysis system, a combined model and assimilated weather observation dataset. Data available at:

- <http://www.esrl.noaa.gov/psd/data/gridded/data.narr.html>

Typical Emissions By Location:

This dataset was created as part of the Smoke and Emissions Model Intercomparison Project (#8-1-7-4) for the Fires Anywhere test case. Data available by contacting the authors.

*Static data layers***Ecoregion boundaries:**

For modeling and analysis purposes, we use both the Bailey (Bailey, 1995) and Omernik (Omernik, 1987) ecoregion polygons. Data available at:

- <http://www.fs.fed.us/rm/ecoregions/products/map-ecoregions-united-states/> (Bailey)
- <http://www.epa.gov/wed/pages/ecoregions.htm> (Omernik).

GACC and PSA boundaries:

We use the geographic boundaries of the National Interagency Fire Center Geographic Area Commands (GACCs) and their corresponding Predictive Service Areas (PSAs). Obtained through the Northwest Coordination Center (NWCC).

Class 1 airshed boundaries, non-attainment areas GIS layers:

Obtained from government web sources:

- Class I areas: <http://www.nature.nps.gov/air/maps/classIloc.cfm>
- Non-attainment area boundaries: http://www.epa.gov/airquality/greenbook/gis_download.html
- Design values by county: <http://www.epa.gov/airtrends/values.html>

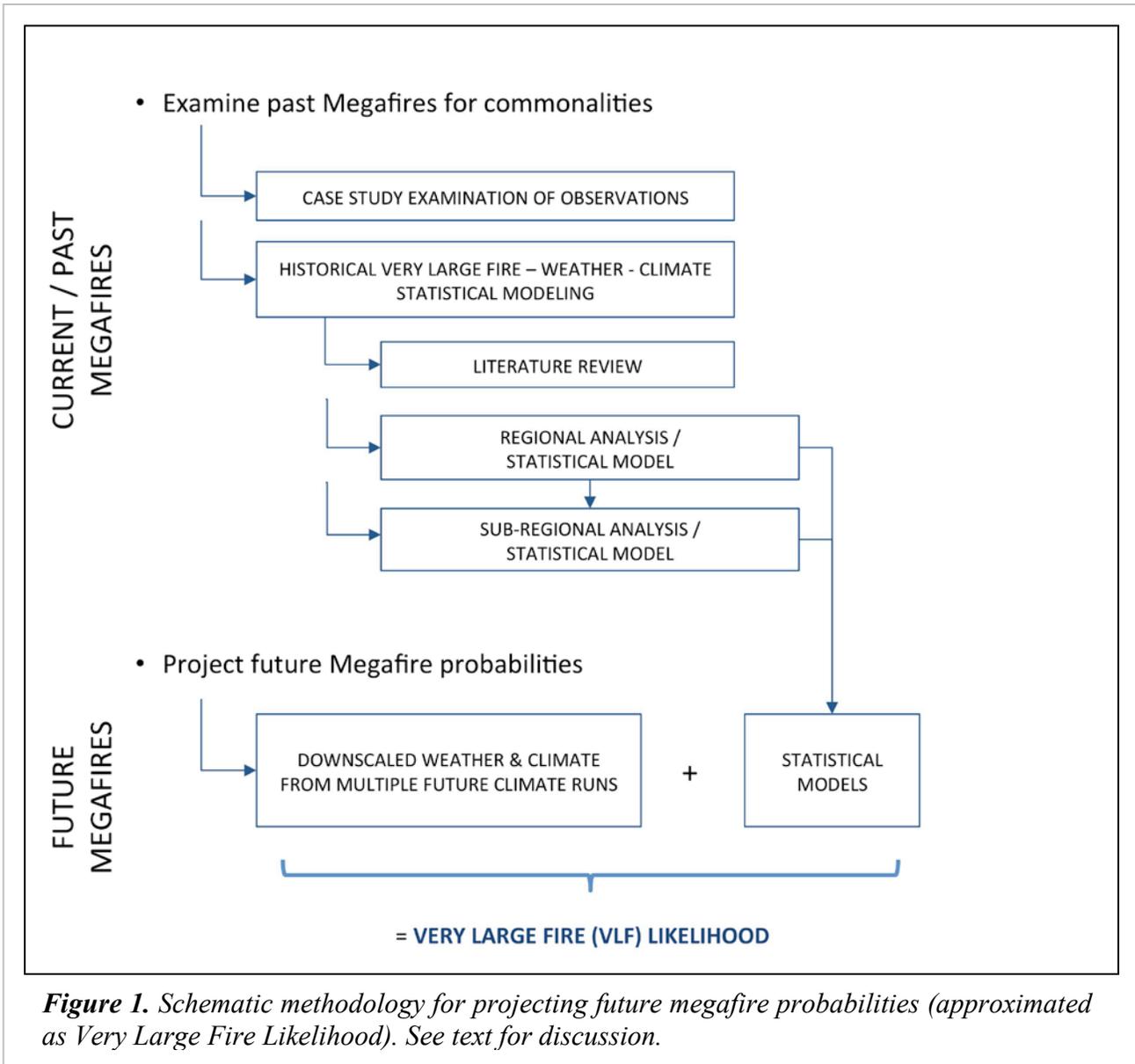
Methods

The overall methodology is described in the following diagrams (Figures 1-3).

We project the likelihood of future Megafires by combining observed relationships between past very large wildfires and climate indices with existing future climate scenarios from multiple CMIP5 climate models (Figure 1). To accomplish this, in order do this, a large amount of work was necessary:

- First, we defined Megafires for use in this analysis. We explored multiple definitions, including fire size thresholds that vary as a percentile of observed fire sizes and static thresholds defined objectively across the landscape. We note that statistical models to predict only the most extreme 1% of observations, e.g., megafires as traditionally defined, are unlikely to be successful. We ultimately used a threshold of > 50,000 acres, defining it as a Very Large Fire (VLF), and built models of these very large fires to understand and approximate the climate factors associated with Megafires. However, prior to adopting this methodology, we performed a case study of a large number of Megafires to look for commonalities in fire progression, growth, size, terrain, management activities, and other factors.
- Second, we created a set of statistical models for the likelihood of a very large fire. Models were based on observed fires and their relationships with vegetation, weather, climate, and other factors. These models were developed at a number of spatial scales.
- Finally, using downscaled future weather and climate information and the statistical models developed here, we projected VLF likelihoods into the future using a number of future climate simulations.

Concurrent with the megafire statistical analysis, we examined the probability that smoke from a fire would reach various kinds of sensitive receptors, based on historical weather (Figure 2). For



each source location, the resulting aggregate map of Smoke Impact Potential (SIP) takes into account the following:

- The typical emissions rate for that location based on local fuel loadings and typical wildfire fuel moisture conditions;
- The typical weather patterns for that location and where it will transport the smoke based on the time of year;
- The sensitive receptors (see below) located in the region where the smoke will be transported.

Several versions of the SIP were created based on the receptors of interest:

- SIP based on impacting human populations;

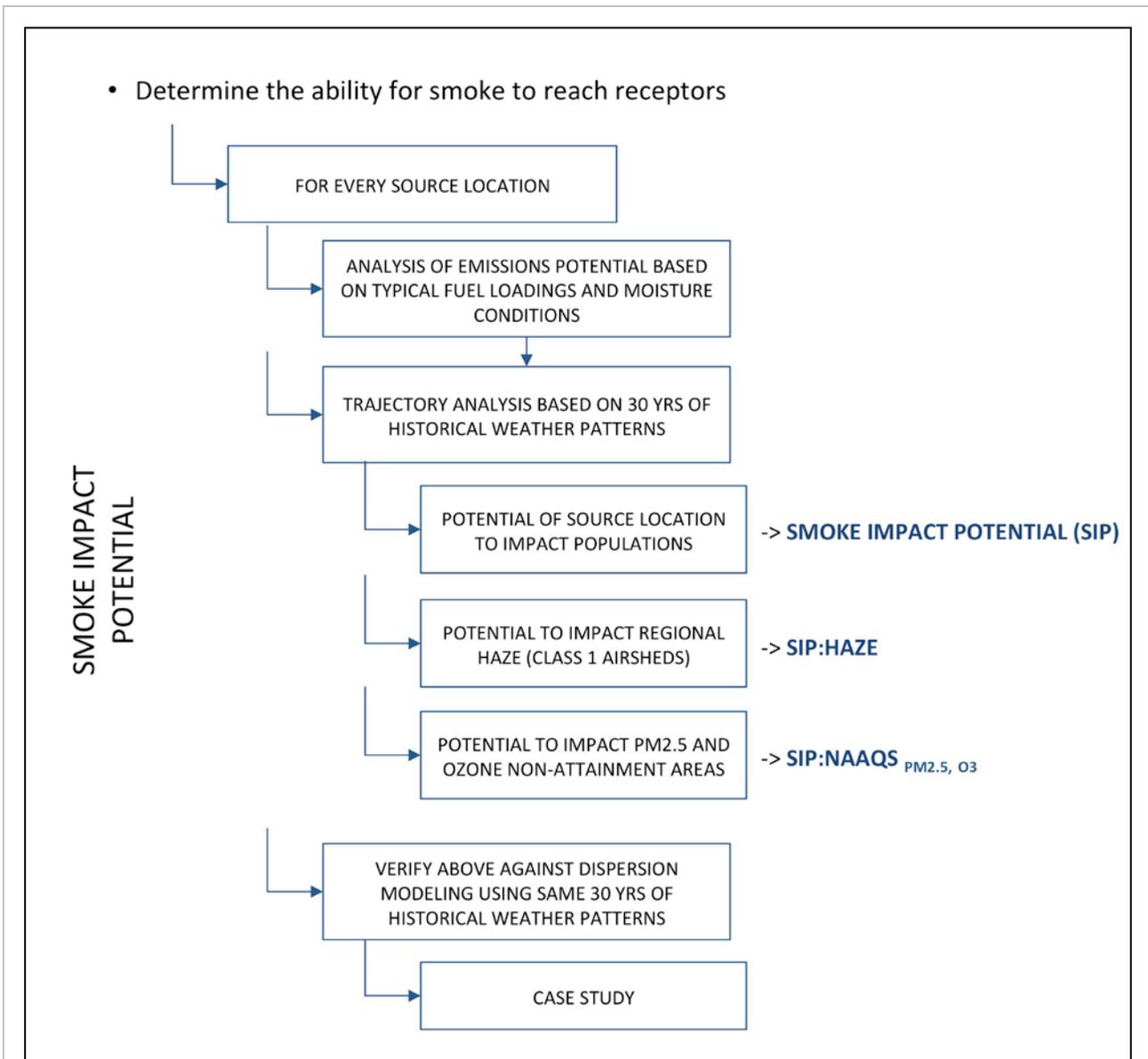


Figure 2. Schematic methodology for determining the ability of source location to impact receptors. Receptor types are human population, Class 1 Airsheds protected under the Regional Haze Rule, and areas deemed non-attainment under the National Ambient Air Quality Standards (NAAQS). Climatologies were determined through trajectory modeling using historical weather and validated against case studies using dispersion modeling. These climatologies are used to create a summary Smoke Impact Potential (SIP) by climatological week (e.g., number of people in transport area for that week). See text for discussion.

- SIP:HAZE based on impacts on Class 1 airsheds protected under the Regional Haze rule; and
- SIP:NAAQS, further separated into PM2.5 and Ozone, based on impacts on areas currently in non-attainment or near non-attainment (within 15% and 30%) areas.

These are discussed further in the relevant sections.

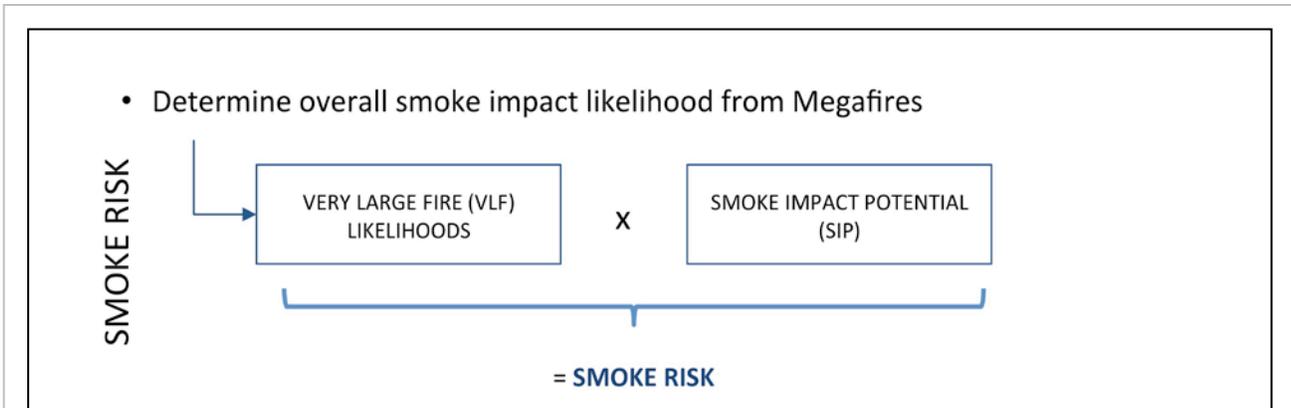


Figure 3. Schematic of creating overall Smoke Risk, based on combining the likelihood of a very large fire (VLF) with the ability of a fire in that location to reach receptors – human populations (Smoke Impact Potential or SIP), Class 1 airsheds for Regional Haze issues (SIP:HAZE), non-attainment areas for PM_{2.5} and Ozone (SIP:NAAQS_{PM_{2.5}, O₃}). See text for discussion.

We then combined the VLF Likelihoods with the relevant SIP to generate an overall Smoke Risk metric (Figure 3). This was done by multiplying the VLF Likelihood at each location and climatological week by the SIP for that location and climatological week:

$$\text{Smoke Risk}_{x,y,clim\ week} = \text{VLF Likelihood}_{x,y,clim\ week} * \text{SIP}_{x,y,clim\ week}$$

Note that Smoke Risk estimated here is a measure of how smoke from the source location (fire location) might impact human populations in the future, both because of the probability of a VLF at that source location and because of the ability of that smoke to be then transported into human population centers. It is not a measure of overall smoke impacts at the fire location.

Summary results comparing the locations with the highest overall risk of a VLF and those with the highest overall Smoke Risk are shown in Section 3.

Summary of Methods Used

This is a short summary of the methods used. For details on the methods, please see the relevant Appendices as well as the published papers stemming from this work.

Defining Megafires

Megafire Definitions Used Here:

- Multiple fire size definitions were tried during the course of this project (Appendix A).
- Various categorical approaches to describe megafires were considered.
- Ultimately we used the following definitions in different aspects of the work:

- Final fire size \geq 50,000 acres
- Final fire size \geq 12,500 acres.

Megafire Definition Case Study:

- 21 megafires were identified (Appendix B).
- Commonalities and differences were examined across various dimensions, including location, fuel type, growth patterns, management (suppression) activities and response, national and regional preparedness levels, among others.

Modeling Megafires and Future Megafire Projections

Statistical Modeling:

- Exploratory data analysis was done before deciding on a statistical technique and the level of aggregation of the data (Appendix C).
- Logistic regression models estimating the likelihood of a very large fire given current weather and fuel conditions were estimated at the regional (Geographic Area Coordination Center, GACC) scale (Appendix D).
- Stepwise selection of covariates was used to build a set of generalized linear models (GLMs) at the sub-ecoregion (60-km) scale (Appendix E).
- Both antecedent and concurrent weather conditions were analyzed.
- Ecosystem types, regions, and other location features were used as conditioning variables.

Future Climate Scenarios and Future Megafire Projections:

- Downscaled weather information from future climate scenarios for 2041-2070 was used.
- The intervening time period (current – mid century) was also examined.
- Downscaling was done for 17 different climate model runs spanning both the RCP4.5 and RCP8.5 scenarios.
- The likelihood of future very large fires was estimated at regional (GACC), Predictive Service Area (PSA), and sub-ecoregional (60-km grid) scales (Appendices E and F).
- Results from these projections were compared with available literature (Appendix G).
- For the sub-ecoregional projections, a multi-model mean was created along with a weekly climatology based on the 30-year future period (2041-2070).
- Monthly and annual values were created for Very Large Fire risk.
- Locations were ranked based on this overall annual Very Large Fire likelihood (see Section 3).

Smoke Impact Assessment (need a reference to Appendix J)

Emissions Potential:

- Typical emissions for each location were calculated using the Fuel Characteristic Classification System (FCCS) fuelbed map and the Consume 4.0 model using typical fuel moisture conditions for the wildfire season at that location (Appendix H).

Trajectory Modeling and Smoke Impact Potential:

- Trajectory modeling results were taken from an existing project (Larkin et al., 2013, JFSP Project #10-S-02-1) and reanalyzed.
- Trajectory modeling was based on a 31-year period (1979-2009) using the North American Regional Reanalysis weather dataset with trajectories released every 6 hours from each of 1926 starting locations across CONUS (Appendix I).
- Trajectories were converted to transfer functions: $T(\text{source location, receptor location})$.
- Impact potential was created by weighting the transfer function by the receptor value (e.g., population) at the receptor location and integrating across all receptors.
- Smoke Impact Potential was created by further weighting the impact potential by the emissions potential of the source

$$SIP_{source} = \sum_{\text{all receptors}} (T_{source,receptor} \times W_{receptor}) \times EM_{source}$$

where T is the transfer function connecting the source and receptor, W is the receptor value (e.g., population) at the receptor location, and EM is the emissions potential of the source.

- Separate SIP analyses were done for:
 - Population (labeled here SIP)
 - Class 1 airsheds (labeled here SIP:HAZE)
 - PM2.5 non-attainment areas (labeled SIP:NAAQS_{PM2.5})
 - Currently designated areas
 - Derived areas based on a 15% and 30% tightening of the PM2.5 standard
 - Ozone non-attainment areas (labeled SIP:NAAQS_{O3})
 - Currently designated areas
 - Derived areas based on a 15% and 30% lowering of the PM2.5 standard.

Overall Smoke Risk:

- Overall smoke risk was assessed by multiplying (scalar multiplication/vector dot-product) the future VLF likelihoods with the SIP maps.
- In doing this, the VLF likelihoods were first aggregated into a multi-model mean and weekly climatology from the 30-year future period (2041-2070).
- Smoke risk was calculated separately on a climatological week basis.
- Monthly and annual aggregates were created by summing and/or averaging over the weekly values.
- Locations were ranked based on the annual mean overall value of Smoke Risk (see Section 3).

Limitations and Caveats

This section outlines the challenges and limitations of our analysis.

- Statistical models predicting the probability of Very Large Fires (VLFs) have the following challenges:
 - VLFs are rare—therefore, there are limited occurrences, making statistical models challenging.
 - Climate precursors and weather drivers may be at different scales.
 - There may be temporal lags between fire weather, fire detection, and fire occurrence.
 - Suppression information was not included in the models.
 - We assumed that processes driving the probability of VLFs in the past are the same as those that will drive the probability of VLFs in the future.

See Appendix C for further discussion.

- To project megafires into the future, we focused primarily on surface variables that were available both from historical analyses and also from future statistically downscaled climate scenarios. This necessarily limited our ability to utilize fire weather indices that require high temporal/spatial resolution (e.g., near-fire, hourly) because these data were unavailable for the future climate scenarios. Daily gridded winds and other variables were used at the best resolutions available, but these are not as likely to have strong predictive value for determining the likelihood of a megafire as more local, temporalized data. This limitation of the current analysis has been identified as a needed next step. Similarly, for the majority of fires used in the statistical analyses, daily growth data were not available, making statistical connections between daily growth and daily/sub-daily weather data difficult to model.
- Future weather patterns were not used for the smoke transport analysis. Smoke transport analysis requires very high resolution 4-dimensional weather information (x,y,z,t) that is not available for most of the climate model runs used. Instead, our analysis disconnects the future megafire likelihood projection from the smoke transport question. Our analysis, therefore, assumes that typical (i.e., prevailing) wind conditions by climatological week remain the same in the future.
- Vegetation succession is not included in the models of future very large wildfires. In projecting future megafire likelihood, we assume that the vegetation type remains constant in a given location. Additionally, we assume that typical fire emissions for a location remain similar to what would occur under present conditions. Vegetation succession is not well understood yet has the potential to greatly influence model predictions. In many ways, this ‘status quo’ vegetation assumption is the simplest available. In most cases, it will tend to underpredict megafire potential.
- Smoke transport from trajectories does not properly take into account dispersion in the smoke plume. A full dispersion model was not used for the Smoke Impact Potential assessment because it would require exponentially more computer time than was available. As it was, over 600 million trajectories were utilized; performing the over 30M dispersion model runs necessary would take an estimated 100+ CPU years of computer time, with similarly increased data storage and data analysis issues. Instead we use full dispersion runs to validate the overall approach here (Appendix K).

Changes Made to Proposed Methodology

Several changes to the proposed methodology were incorporated as the research progressed, in order to address the challenges we encountered. These include:

- We were unable to objectively identify a threshold of climate, weather, or fire danger indices that separated megafires from non-megafire large (>1000 acre) fires. Whereas megafires were far more probable during certain environmental conditions, the diversity of conditions during which megafires were initiated and during which they grew made such an effort unfeasible. Instead, we used a statistical methodology for estimating the probability of a VLF, given particular combinations of indices.
- Similarly, the ability to estimate screening vs. scaling functions as envisioned in the original document has been modified. Currently, the statistical modeling uses both an *occurrence of large fires* component as well as a *probability of a megafire given the occurrence of a large fire* component. These are conceptually related to the proposed screening and scaling functions.
- While the top 5% of fires for each National Predictive Service Area (PSA) was examined, in many cases the top 5% of fires for a given PSA included relatively small fires (e.g., in western Washington fires of ~50 acres). This makes distinguishing conditions that separate these fires from other “large” fires nonsensical or intractable. Thus, this component of the project was eliminated in favor of the VLF definitions used here.
- The climatological trajectory database used here is of forward trajectories from a grid of starting locations rather than backwards trajectories from a set of sensitive receptors. This became necessary because of the methodological issues discovered in back-trajectory modeling near mountain ranges as discussed in the Final Report for Project #10-S-02-1. This change necessitated considerable additional work – both due to the massive size of the forward trajectory database compared with the backwards trajectory database, and the need to create smoke impact transfer functions that show the patterns of impacts from each source location.

3. KEY FINDINGS

The project's main goals were to develop, first, a ranking of areas where 'megafires' will be more likely in the future, and, second, a re-ranking based on the capability of these projected megafires to impact populations. Of course, such an endeavor necessarily involves a great many steps with significant intermediate work and results, as discussed below. However, for greater simplicity and clarity in this report, we first present the main conclusions and then discuss the analyses by which these results were generated.

The sections below present (a) summary key findings based on the ultimate ranking of both future mid-century megafire likelihood and the smoke impacts from future megafires; and (b) select key findings from component parts of the overall project including findings on the definition of a megafire, when and where megafires have occurred, what key weather and climate variables were found to be most related to megafires in the statistical modeling done, what these statistical models tell us about megafires in the future, and what can be said about smoke impact potential across the country.

SUMMARY RANKINGS

Summary rankings: Megafire likelihood

Figure 4 shows the overall ranking of locations across the country based on future VLF occurrence. Overall risk is presented normalized to the highest value found in any cell. The figure is a summary of the findings of the project across all future climate model runs and scenarios. It necessarily obscures significant additional information available by examining the climatological monthly cycle of the results, the details of the statistical model, and intermodel differences between individual climate runs (see additional results and discussion additional Key Findings sections below). Additionally, while specific individual grid cells are ranked, at this overall level, the results are most robust when regional areas of high or low ranking are compared, rather than the specific numeric rank of any individual cell.

- **The highest ranking areas in terms of overall Very Large Fire likelihood are found across the western U.S. including the Rockies, Cascades, Sierra-Nevadas, and Great Basin regions.**
- **The eastern U.S. shows smaller overall likelihoods as compared with the western U.S. However, the increase in likelihood compared with current conditions is still significant (see below).**
- **Outside of the west, the areas with the most likelihood are found in:**
 - **The upper Minnesota / Wisconsin / Upper Peninsula region;**

- **The southeastern seaboard including the Carolinas, Georgia, and Florida; and**
- **The Ozarks.**

Note: While the Ozarks are ranked high, this higher than expected rank (#46) appears to be an artifact of the statistical methodology used.

Summary rankings: Smoke risk

Figure 5 shows the overall smoke risk derived from connecting the overall likelihoods with the typical ability for a fire in a given region to emit smoke as well as the climatological transport patterns and the potential downwind population. This can be considered a summary re-ranking of the results found in Figure 4 based on the ability of a fire in each location to impact population. As in Figure 4, the results are normalized against the highest value found in any cell (see Section 2 for methods and caveats).

- **The overall pattern is somewhat similar to that found for overall likelihood of Very Large Fires, but areas that are either climatologically upwind of population centers and/or have the potential for large organic consumption are ranked higher.**
- **California with its large population becomes highlighted, as well as both areas upwind of population centers in Nevada.**
- **The upper Minnesota region ranks higher than previously due to the potential for very large emissions from peat fires.**
- **Significant portions of the Rockies are reduced in rank, excepting those areas near population centers (e.g., Denver).**
- **The Ozarks are elevated in rank due the potential for smoke to transport to both Midwest and eastern population centers.**
- **The eastern seaboard retains areas of significant overall risk, but the rankings for these regions—particularly those with the potential for significant deep organic consumption—are tempered due to the prevailing westerly winds that tend to cause smoke to transit out into the Atlantic.**

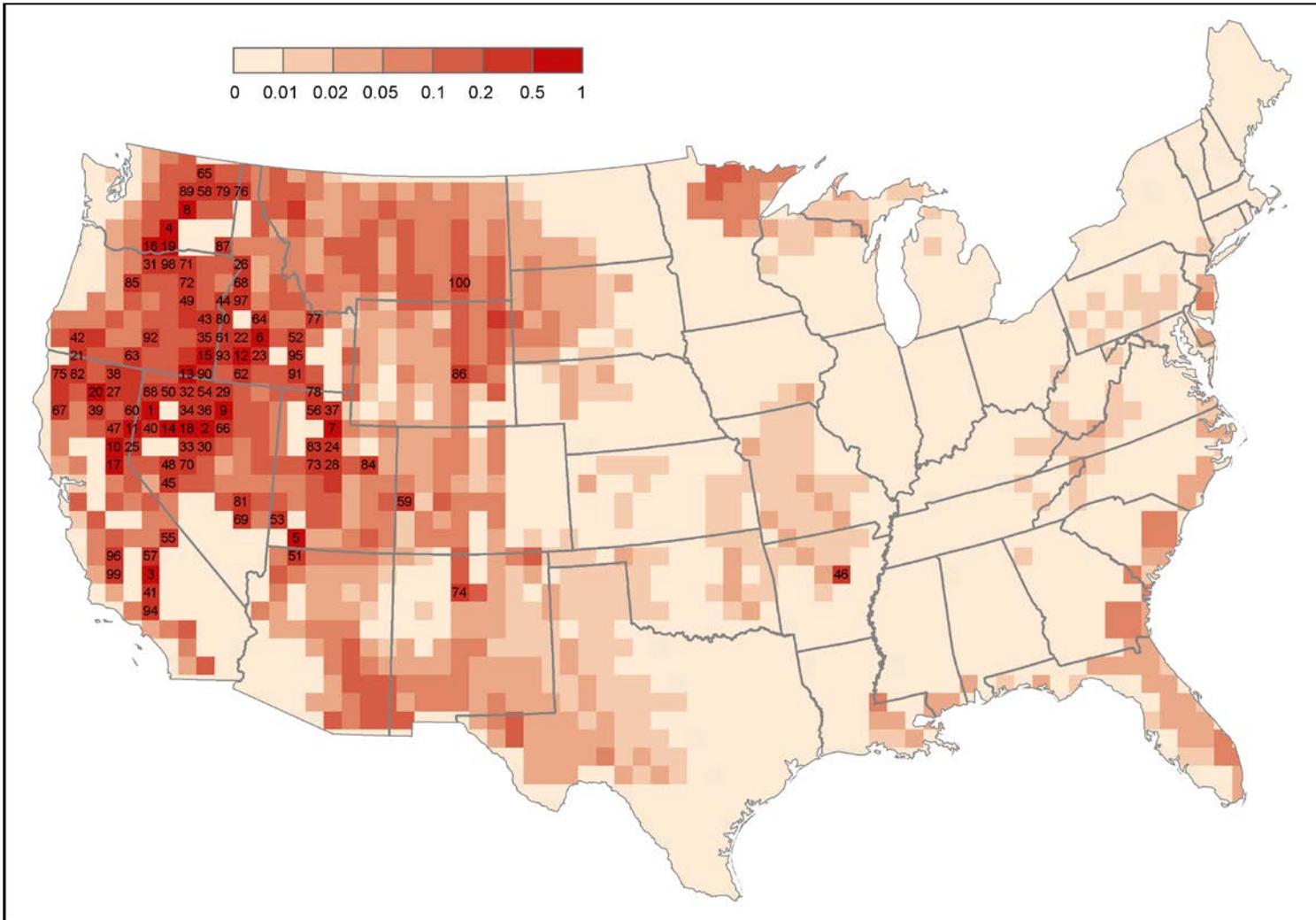


Figure 4. Relative mean annual likelihood of Very Large Fires (VLFs ≥ 12.5 k acres) occurring in the future. Based on downscaled weather and climate information from 17 future climate model runs of the period 2041-2070 using statistical fire model developed for this project. All cells normalized to the highest likelihood in any cell (=1). See Methods for discussion. Results are aggregated to a 64km grid and normalized to the maximum value at any grid cell (16% chance of a VLF occurring per year per grid cell 4096 sq km). The top 100 grid cells are listed.

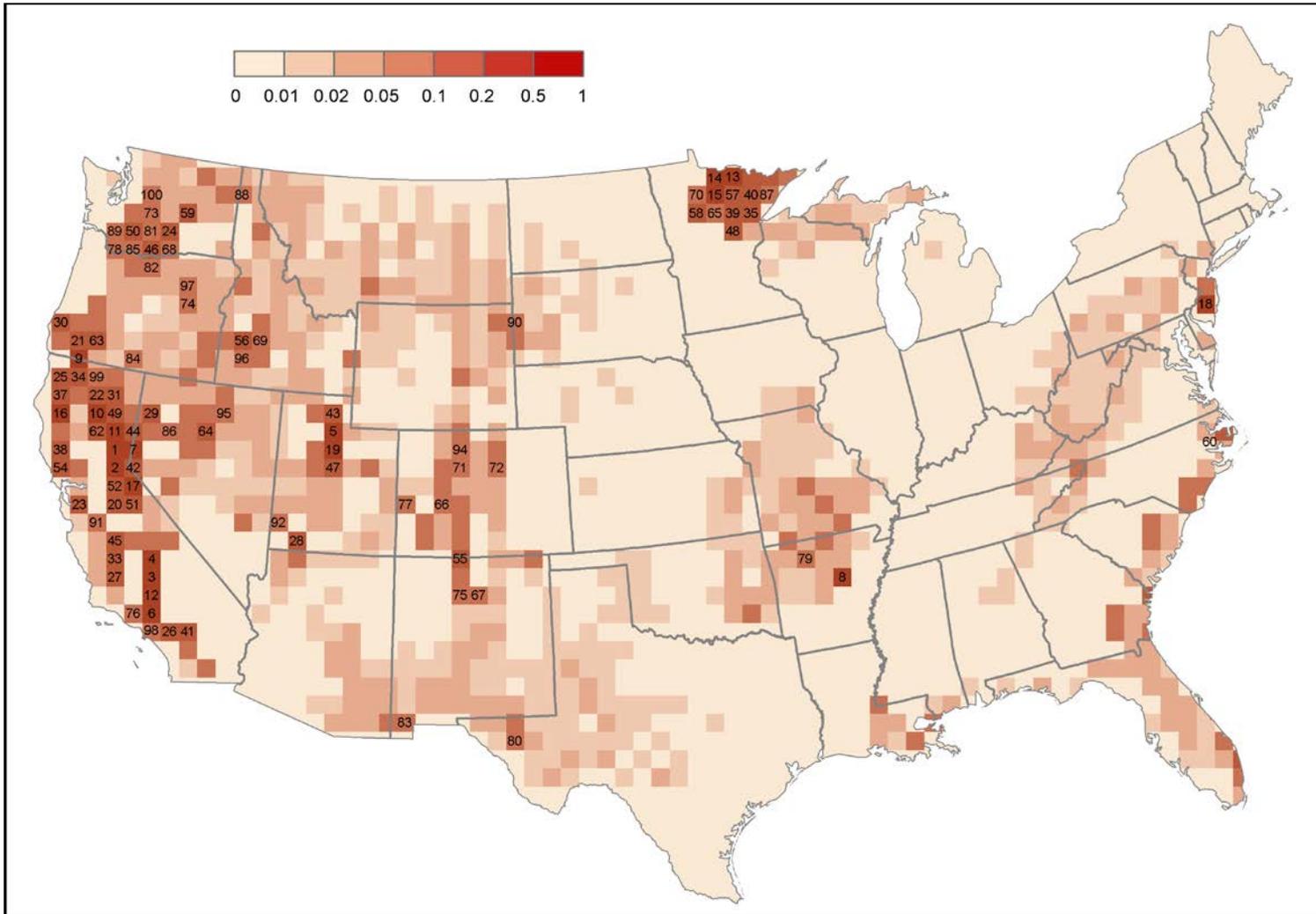


Figure 5. Relative mean annual Smoke Risk from Very Large Fires (VLFs) in the future. Here Smoke Risk = VLF Likelihood * Smoke Impact Potential (SIP). All cells normalized to the highest risk in any cell (=1). VLF likelihood is shown in Figure 4. SIP based on analysis of historical weather patterns and the potential for population exposure. See Methods for discussion. Results shown aggregated to a 64km grid and normalized to the maximum value at any grid cell. The top 100 grid cells are listed.

DEFINITION AND HISTORICAL PATTERNS

What is a 'megafire'?

- **The term megafire is ill-defined.**
- **No consensus definition of a megafire exists.**
- **A case study of 21 megafires showed:**
 - **Some commonalities:**
 - **Size**
 - **Occurred during anomalous drought or fire danger conditions**
 - **Many burned most of their final size within 10 days**
 - **Significant differences:**
 - **Duration**
 - **Fire progression**
 - **Cost**
 - **3 different management pathways.**
- **Very Large Fires can be used as a proxy for megafires.**

One of the major issues with this work was defining the term megafire. Generally taken as very large fires with significant socio-political impact, the term megafire is ill-defined, and no consensus definition in the literature was found. (See Appendix A for a more complete discussion).

Using a case study of 21 megafires that have some agreement within scientific and management circles, we examined whether there were distinct commonalities in what occurred, including fire behavior, firefighting strategies and staffing, and other issues (see Appendix B). This case-study approach found three different clumps of management pathways in the suppression of these fires - a high level of burnout operations, low priority delayed response, and low priority limited suppression resources.

To avoid issues with definitions, we use final fire size to create an objective definition for VLFs and use these as a proxy for so-called megafires. While this simplification ignores the socio-political aspects of 'megafire,' it provides a replicable objective definition that generally agrees with expectations of what the term megafire means. Two definitions are used here for VLFs, although the results found are substantially similar regardless of which definition is used.

Where and when have megafires occurred?

- **Very Large Fires have been observed in recent decades across large parts of the United States, with geographic hotspots in southwestern California, the northern Great Basin, and central Idaho mountains.**

Using satellite-derived burned area from the Monitoring Trends in Burn Severity (MTBS) database from 1984-2010, we mapped out the location of all large fire and VLF according to the definitions discussed above (Figure 6). While VLFs were found across most of the US, they were rather sparse east of the Mississippi, with a cluster of VLF in the southern Appalachians near the Kentucky-West Virginia border that burned during the autumn and a cluster in Florida that occurred throughout the year. VLFs were observed in the southern Great Plains primarily in the spring. Nearly all of the fires in the western US from the Rockies to the Pacific coast occurred from May through October. The highest density of VLFs was found in southwestern California, the northern Great Basin covering northern Nevada, eastern Oregon and southern Idaho, and the mountains of central Idaho. Other regions of high VLF density included the eastern slopes of the Cascades, northern Sierra Nevadas, and the northern Rockies. These same areas also had the highest density of large fires exceeding 1,000 acres.

Fires exceeding 50,000 acres in size were similarly concentrated in regions that experienced VLFs. The greatest concentration of such fires was in the northern Great Basin where invasive annual grasses such as *Bromus tectorum* have increased fuel connectivity and the potential for extremely large wildfires when environmental conditions are favorable. The peninsular and

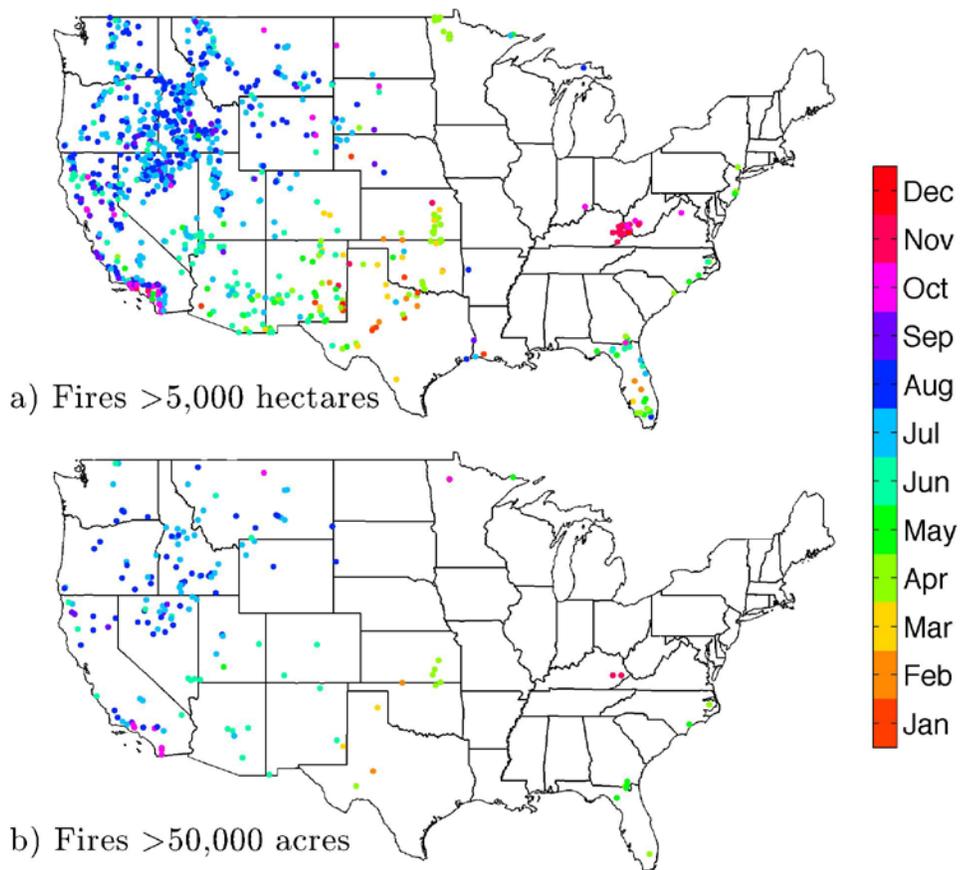


Figure 6. Location and timing of VLF (>12,500 acres) and fires greater than 50,000 acres for the MTBS period 1984-2010. The month of fire discovery as reported by MTBS is color-coded to denote the timing of the fire.

transverse ranges of southwestern California experienced numerous fires exceeding 50,000 acres over the MTBS time period including fires that burned during the summer (e.g., Zaca fire of 2007), and Santa-Ana wind driven fires in October 2003 and 2007.

- **Very Large Fire occurrence has grown over the past 3 decades.**

The number of VLFs and the amount of area burned in VLFs increased over parts of the US from 1984-2010 (Figure 7). While the number varies by geographic area, nearly twice as many VLFs and over 150% more area burned in VLFs occurred during the second half of the MTBS record (1998-2010) than the first half (1984-1996) for the contiguous US. A larger rate of increase in the area burned in VLFs (160%) over the 27-year record versus all large fires mapped by MTBS <5kha (100%) suggests that VLFs have increasingly contributed to annual burned area. Collectively, the increase in both number and burned area in VLFs is likely a key contributor to the overall increased burned area observed over the period of record.

A strong relationship exists between total annual burned area and the fraction of annual area burned in VLFs for the US. Years with large burned areas (e.g., 1996, 2000, 2006, 2007) had an anomalously high portion of area burned in VLFs. Regional climate anomalies are the

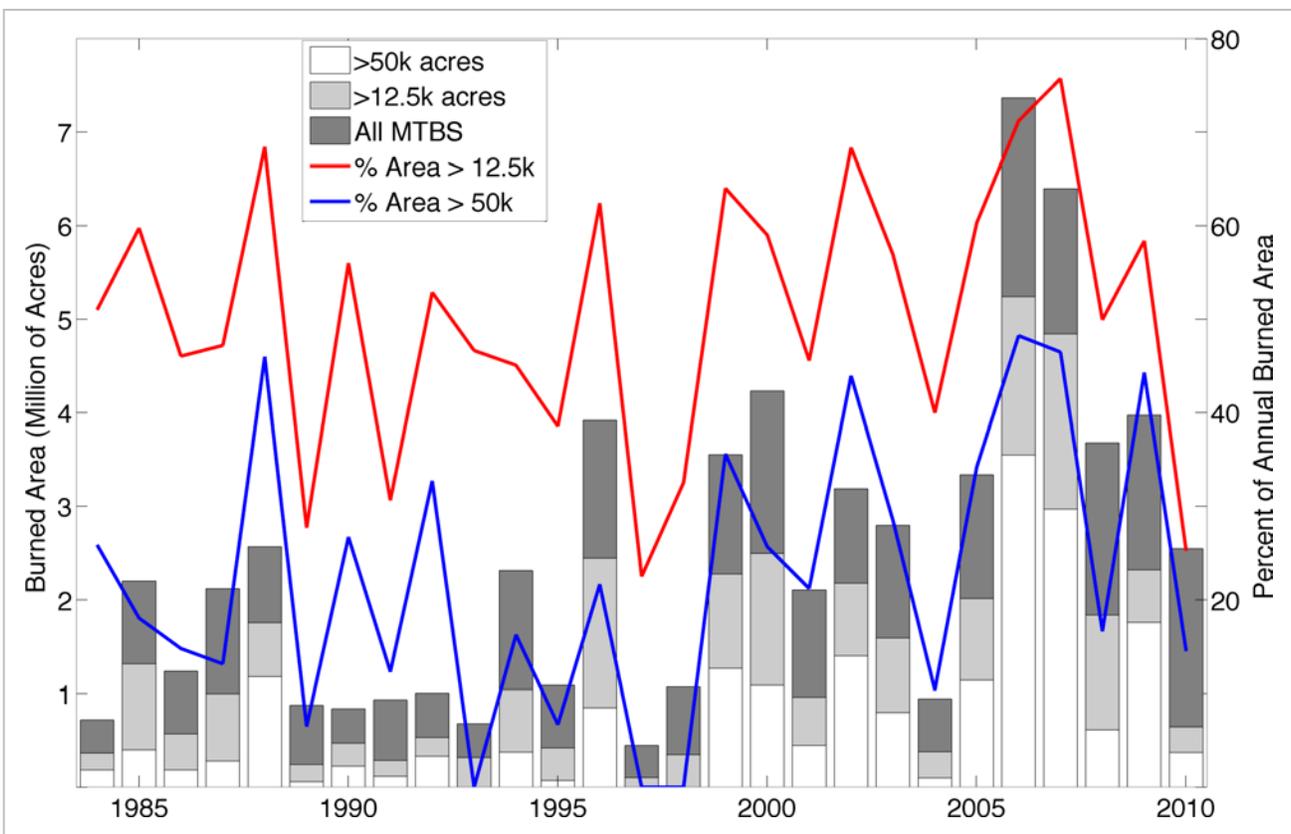


Figure 7. Annual burned area for the contiguous United States from MTBS fires from 1984-2010 for all fires, Very Large Fires (VLFs) exceeding 12,500 acres, and VLFs exceeding 50,000 acres. The red and blue lines show the percentage of annual burned area in VLF exceeding 12,500 acres and 50,000 acres, respectively.

predominant driver of year-to-year variability in burned area and are hypothesized to be an important factor associated with VLF occurrence.

- **There are no universal conditions under which Very Large Fires have occurred.**

VLFs have occurred across a variety of ecotypes, climates and meteorological conditions making it challenging to define a clear niche under which such fires occur. Among the factors that influence the location and timing of VLFs are fuel type, antecedent climatic conditions, and concurrent fire danger conditions. Although the distribution of VLFs is significantly influenced by these factors, VLFs were observed across a comprehensive set of environmental conditions.

While an individual fire may burn in heterogeneous fuels, we broadly classify fires that occurred in forested versus non-forested systems based on the level II Omernik ecoregion in which they fall. Over half (56%) of all VLFs and fires greater than 50,000 acres occurred in non-forested ecoregions. The characteristics of VLFs varied substantially between these two ecotypes with generally longer-duration fire events in forested systems versus short-lived rapid spread events in grassland and non-forested systems.

Climatic thresholds did not appear to universally work in distinguishing VLFs. Over 80% of VLFs generally burned in weeks when 100-hour dead fuel moisture was less than 10% (compared to 55% of all MTBS fires). However, a few VLFs started when fuel moistures would otherwise be high enough (100-hour fuel moisture > 16%) to reduce fire activity, only to grow at later stages when conditions became more favorable. Similarly, longer-term drought conditions identified through the Palmer Drought Severity Index generally were aligned with VLF occurrence. However, these relationships were far from universal in nature.

Finally, we based our analysis on VLFs that occurred over the 1984-2010 period. However, we acknowledge that the absence of mapped VLFs in a region does not restrict them from occurring there. For example, through fire atlases and tree-ring records we know that extremely large fires have occurred in places such as the Idaho Panhandle and western Washington where no VLFs were mapped.

- **But Very Large Fires are commonly driven by climatic and meteorological conditions.**

Despite the lack of well-defined thresholds under which VLFs occur, there were common factors under which most VLFs occurred. Specifically we focus on the time-varying contributions from antecedent climate as well as shorter-term fire danger and fire weather conditions. While the influence of antecedent moisture realized through the Palmer Drought Severity Index (PDSI) varied between ecoregions, VLFs occurred during prolonged periods of elevated fire danger (e.g., Energy Release Component, Duff Moisture Content) in both forested and non-forested fuels. When comparing VLFs to all fires mapped by MTBS it is clear that VLFs burned during substantially more acute fire danger periods than other large fires. As an example, a lead-lag

composite of Energy Release Component (ERC) percentiles for the fire centroid of over 7000 fires in the western US is shown in Figure 8, separated by fires burning in non-forested and forested systems. For VLFs, the average ERC in forested systems is near the 95th percentile from the discovery date to nearly three weeks later, creating a prolonged opportunity for fire spread and likely making suppression a challenge. By contrast, other large fires reach a lower percentile near the discovery date with diminished fire danger quickly thereafter, allowing for suppression activities.

While VLFs disproportionately occurred during anomalous conditions, such conditions were not a requisite for VLFs. Rather, some VLFs occurred under conditions that from a purely atmospheric and climatic perspective would be classified as normal. Likewise, extreme conditions (e.g., high fire danger, long-term drought) did not always cause a VLF.

Unlike the similar relationships between fire danger indices and VLFs in forested and non-

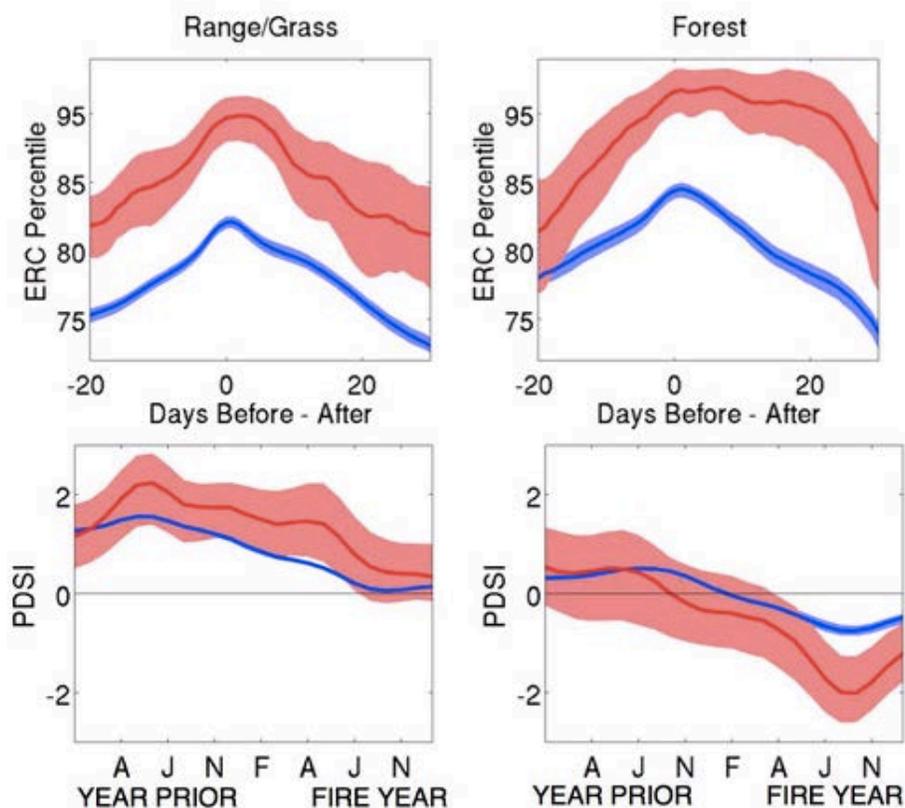


Figure 8. Composite of Energy Release Component (ERC) percentiles taken from the centroid of over 7000 fires that burned in the western US from 1984-2010 from MTBS. ERC percentiles were calculated at the local level and represent percentiles over the entire year (not just the fire season). A composite is separately shown for fires that burned in non-forested ecoregions (left) and forested ecoregions (right) and separately for VLFs (red) and other large fires (blue). The shading represents the 95% confidence interval of the mean. The bottom two plots show composite PDSI from January a year prior to the fire year through November of the fire year.

forested systems, relationships between VLFs and PDSI varied significantly across these systems. In non-forested systems, PDSI was anomalously positive immediately prior to the commencement of the fire season for VLFs versus other large fires, likely linking the increased accumulation of biomass in the previous year and possibly in the spring immediately preceding the fire year to the likelihood of large fires. Conversely, PDSI was anomalously negative in forested systems concurrent to VLFs versus other large fires. These relationships agree with much of the prior research linking interannual variability in burned area to climate, which is not surprising given that much of the area burned during big fire years occur in VLFs.

Overall, these relationships were generally applicable to regions across the eastern United States as well. In general, we found that the combined influence of interannual moisture variability, sub-seasonal drought stress and fuel moisture, and fire weather extremes were most influential in the occurrence of VLFs. For example, nearly 60% of all MTBS fires in Florida were VLFs when PDSI was below the 20th percentile, ERC was above the 85th percentile (averaged 10-days before to 10-days after fire discovery) and average measures of the Fosberg Fire Weather Index exceeded 2 standard deviations within 10-days after the fire discovery date. Thus, in many ecoregions, synchronized long and short term conditions were considered critical for capturing the timing of VLFs. These factors, which notably echo the conditions for extreme fire behavior (Werth et al., 2011), were used in our subsequent modeling studies.

We focused primarily on top-down drivers of VLFs, acknowledging that biophysical bottom-up factors such as topography and vegetation as well as human factors such as ignition sources, access to suppression, prioritization were also important. Within some ecoregions at the top-down scale, we did find that water balance metrics such as climatic water deficit and precipitation seasonality were important criteria in identifying regions within an ecoregion prone to VLF occurrence. Topographic complexity, defined as the standard deviation of elevation within a fire perimeter, was strongly linked to overall fire size in most ecoregions, suggesting that additional more spatially resolved modeling could improve upon the modeling work reported here.

We hypothesized that VLFs may be predisposed to occurring when suppression resources are depleted due to widespread fire activity across multiple GACCs. Using daily National Preparedness Levels (PL) from 1990-2010 we found that PL were significantly higher during VLF. Given the spatial scales over which climate anomalies influence wildfire potential, it is unclear whether this relationship is purely independent.

MODELING MEGAFIRE PROBABILITIES

Overall Findings

- **Modeling Very Large Fire ('megafire') probabilities is difficult due to limited events and scale mismatches.**

There are significant challenges in creating statistical models of megafires/VLFs. These include both the limited number of events with which to create a statistical model and the temporal and spatial scale mismatches between the size of megafires/VLFs and weather and climate data available to characterize them. For example, limited availability of reliable daily growth data in historic records makes it difficult to compare fire growth with weather data. Most prior analysis and modeling has been conducted using aggregated fire and climate data over broad geographic and temporal scales.

Regional Scale Model Findings

- **Key mechanisms vary by region / GACC.**
Broad-scale ecological mechanisms predictive of the risk of a large fire evolving into a very large wildfire differ by GACC. Within each GACC, the risk of a large fire becoming a very large fire is associated with identifiable climatology and can be reasonably well predicted by considering one or a combination of fire indexes just before, during, and up to three weeks after ignition date.
- **No single fire index was useful in every GACC.**
Indices of fuel moisture were found in the best model for every GACC except Southern California where large wind-driven fires during the fall predominate. Air temperature was positively associated with particularly large changes in very large fire risk in three of the eight GACCs.
- **Reasonable predictive skill was found in all regions.**
For all GACCs, a combination of typical fire index variables provided reasonable predictive power.
- **In the regional aggregate, what happened after the fire started was more important than what happened before.**
In only one region did the best model of risk of very large fire include a fire index observed before the ignition week. Fuel moisture variables were most commonly included during ignition week but in some cases fuel moisture as well as burning index,

duff moisture, energy release component, temperature and PDSI recorded up to three weeks after ignition date influenced the odds of a large fire becoming a very large fire. However, we did not consider subregional variability within a GACC such as contrasting fuel types and climate anomalies; there is clearly a need to conduct a more spatially representative modeling effort.

Ecoregion / PSA Scale Findings

- **The statistical model of Very Large Fires, on average, is able to selectively pick out weeks and spatial locations where Very Large Fires have occurred.**

Synoptic variability was found to be a significant driver of VLF occurrences, especially in non-forested ecoregions where rapid fire spread is favored by extreme fire-weather, as, for example, during Santa Ana wind-driven fires in Southern California and grassland systems in the central US. However, the metrics of short timescales of synoptic variability examined may be insufficient to predict VLFs in forested ecoregions such as Western Cordillera where fires typically grow over a longer time period; alternative metrics of ridge breakdown and short wave passage with widespread lighting may need to be developed and examined. Here, sub-seasonal drought viewed through ERC was a key predictor of VLFs in these flammability-limited ecoregions. Concurrent long-term drought described by PDSI was a complementary predictor in the Appalachian forests and Western Cordillera. These results concur with previous climate–fire linkages and the longer time period under moisture stress required to increase landscape flammability in ecosystems dominated by large-diameter trees. Antecedent moisture availabilities were a significant predictor in some fuel-limited ecoregions reinforcing heightened fire activity that corresponds to increased fuel biomass and connectivity a year following pluvial conditions.

In general, VLF probabilities reach their highest amplitude during the spring in the eastern half of the country, the southwestern US during May and June, and much of the interior and northwestern US in mid to late summer (Figure 9). The mean number of VLF weeks expected was highest across the western US between May and September, consistent with the observed distribution of VLFs and their timing.

As our models do not include ignition sources, or other bottom-up factors (e.g., fuel variability and connectivity), and incorporate predictors with strong spatial autocorrelation, they should not be expected to capture the exact location of the fire, but rather local-to-regional enhancements in likelihood probability (P). A temporal composite analysis of voxels reporting VLF-weeks shows peak P during the week of fire discovery (200% above climatology) with enhanced probability in the weeks prior to and following as expected with the serial correlation of many of the predictors used.

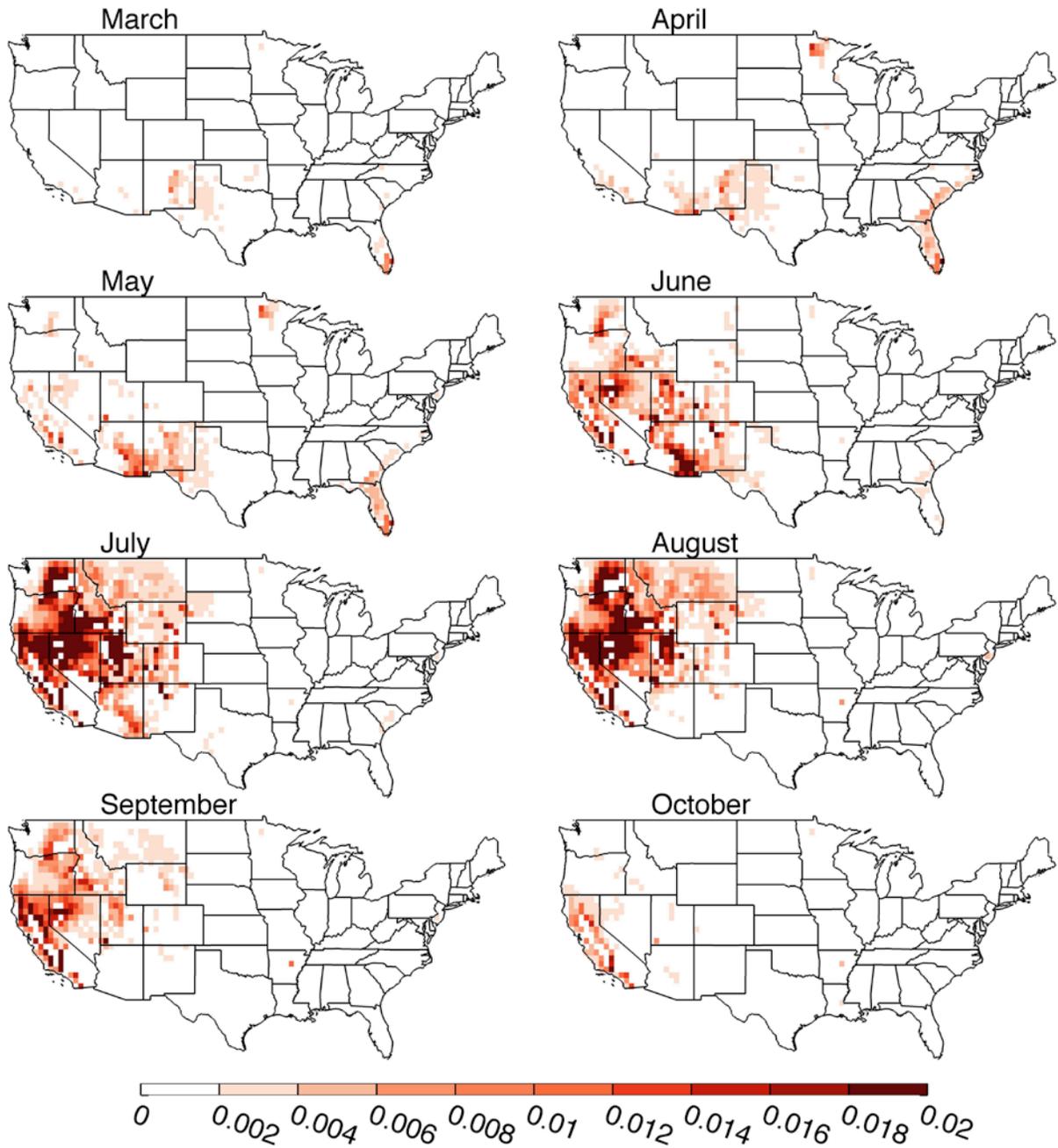


Figure 9. Mean monthly number of expected VLFs per 10,000 square km averaged over the 1984–2010 period from climate–fire model outputs using aggregated observations from Abatzoglou (2013).

- **Climate conditions have become conducive to Very Large Fire occurrence over the past three decades.**

A positive trend in mean annual P was observed over recent decades across much of the western half of the US, but also across some regions in the east, including the Southeast coastline and much of Florida. Likewise, an increase in VLF occurrence has been documented in most southern ecoregions. Increased VLF probabilities over the last three decades are consistent with observed increases in burned area and the number of large fires in recent decades, particularly across the western US. It is important to point out that our observed trends in P clearly isolate climatic conditions as becoming more favorable for VLFs, thereby removing confounding factors such as fire suppression and management as contributors.

Most notable was the widespread increase in probabilities across the southern two-thirds of the western US, where our model estimated a 132% linear increase in probabilities over the 27-year MTBS period. This region has observed a pronounced increase in warm-season ERC and vapor pressure deficit over the last three decades in addition to reduced precipitation in the southwest that collectively promote chronic moisture stress and increased fire potential, particularly in forested systems. A significant increase in probabilities was also found across the southeast US, supporting the increase in VLFs in Florida over the period of record. Whereas fuel buildup and fire management have been attributed to widespread changes in fire activity and the number of large fires, our results suggest that the atmosphere has become more conducive to VLF occurrences in recent years.

Modeling limitations

- **Modeling rare events such as Very Large Fires requires additional measures to ensure robustness.**

Models describing rare binary events are, by definition, designed from small samples, and consequently are often imbalanced, over-fitted, and may suffer from not being robust. Therefore, additional procedures are required to ensure stable and reproducible models. We employed resampling methods in model development and cross-validation to assess model robustness. We used GLM with a stepwise regression given their ability to model binary data. Models were developed for each GACC region and each ecoregion acknowledging regional differences in the biophysical drivers manifest through vegetation and climate, as well as human factors (e.g., ignitions and suppression). Measures to develop statistical models through resampling techniques improve model stability and overcome some limitations of modeling relatively rare events (i.e., large imbalance between events and non-events).

- **Modeling does not account for all factors that contribute to Very Large Fires.**

Our models incorporate predictors with strong spatial and temporal autocorrelation inherent in atmospheric factors but ignore ignition sources. Hence, these models should not be expected to predict the exact location and timing of VLFs, but rather local-to-regional variations in the

probability of VLF occurrence. Model development at finer spatial scales suffers from limited sample sizes of VLFs and lack of ignition sources. However, finer scale analysis that includes both top-down variables, as considered here, and bottom-up variables including fuel types, human factors (e.g., population density, road networks) and land management units may help elucidate additional spatial detail. Furthermore, fire growth and the development of VLFs may also be a function of widespread fire activity that curtails suppression resources. Finally, changes in ignition patterns and frequency resulting from changing distribution of lightning and human factors may contribute to VLFs in ways other than modeled here.

PROJECTING FUTURE MEGAFIRES

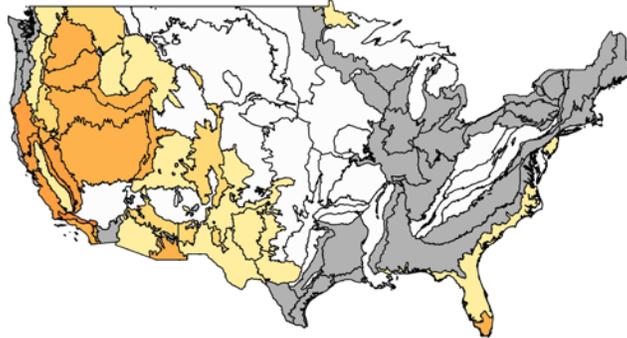
- **A significant increase in Very Large Fire potential is projected under future mid-century climatic conditions.**

Historical climate experiments that used downscaled climate for 1971-2000 from global climate model output simulate a general pattern and magnitude of VLF activity across the US as in the observed record. It is unreasonable to expect a perfect match between modeled historical climate and observed climate and their impacts on VLFs as fire ignitions are semi-random in nature and climate simulations are not designed to mirror decadal to interannual variations in observations. However, the model results are encouraging.

Significant changes in VLF potential are simulated between future climate experiments run for the mid-21st century using a business-as-usual emission scenario (RCP8.5) and historical climate experiments at the ecoregions level III level (Figures 10 and 11) and at the Predictive Service Areas (PSA) level (Figures 12 and 13). Projected changes in climate are simulated by 17 CMIP5 models that were statistically downscaled across the contiguous United States. The models simulate strong warming and, for much of the region, increases in fire danger (e.g., ERC) during the core fire season (Figures 11 and 13). As these variables were selected as predictors in many ecoregions, models run with future climatic conditions simulate a large increase in VLF probability.

Geographic variability in changes in VLF potential were due to both the sensitivity of the model to individual climatic parameters and the specific climate change projections. The largest relative increases in VLF potential were found across the northern tier of the US, where the historical probabilities were low. Conversely, the largest absolute changes are projected for regions across the western US already prone to frequent VLF potential. For much of the western US, the models showed strong agreement of increases in VLF potential.

a) Historical VLF potential (multi-model mean)



b) Future VLF potential (multi-model mean)

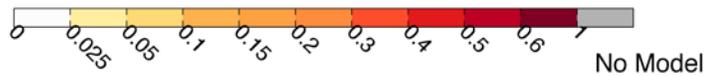
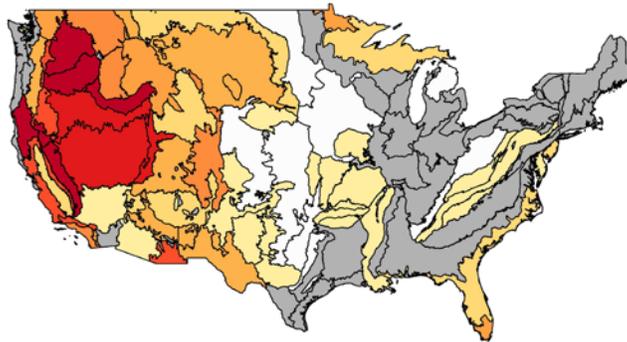


Figure 10. Multi-model mean annual number of VLF weeks per surface unit of 10,000 square kilometers for historic climate experiment (top, 1971-2000) and mid-21st century climate experiment (bottom, 2041-2070) at the ecoregions (level III) level. Gray regions indicate regions with no or insufficient number of VLFs to build robust models.

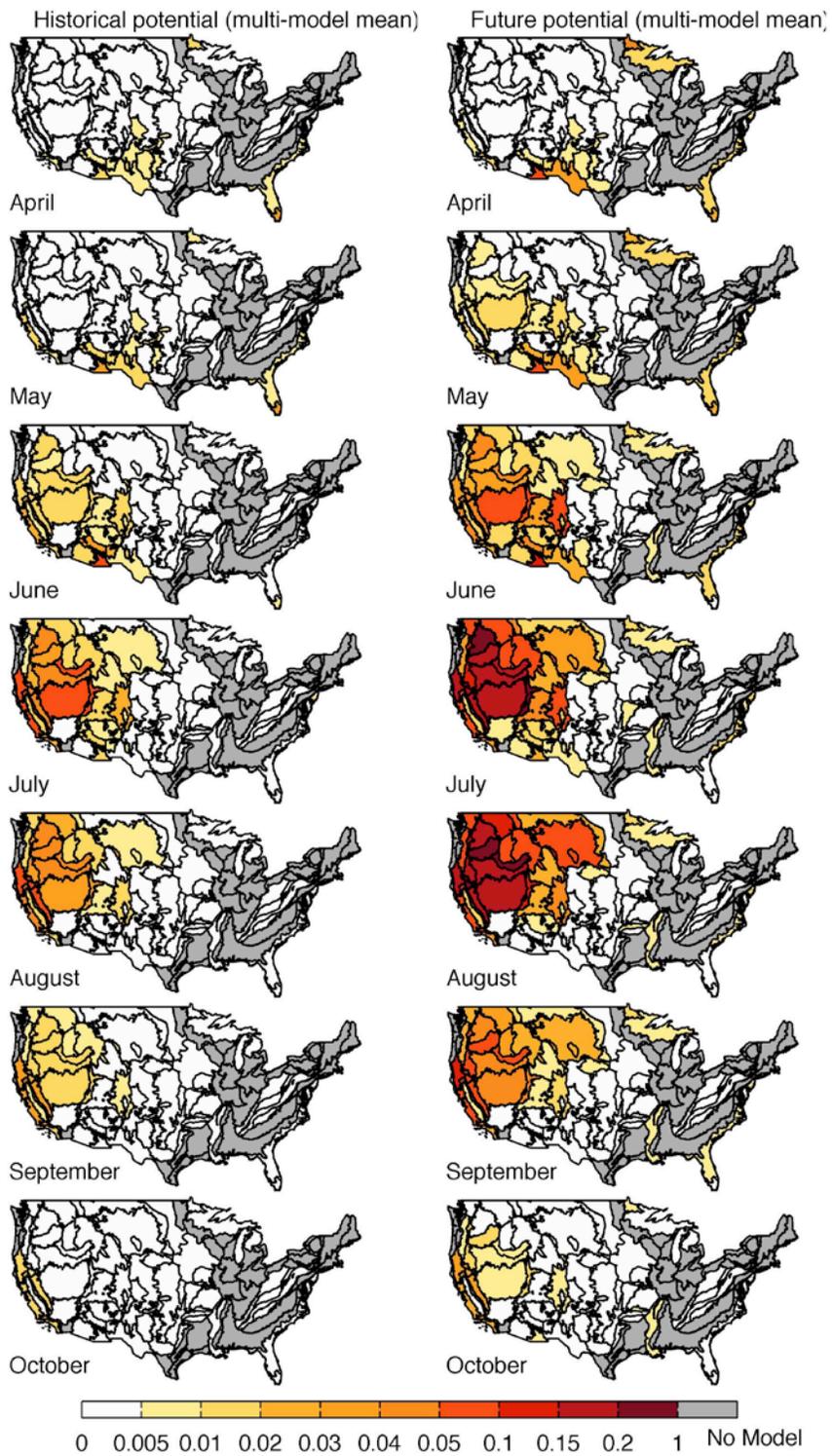
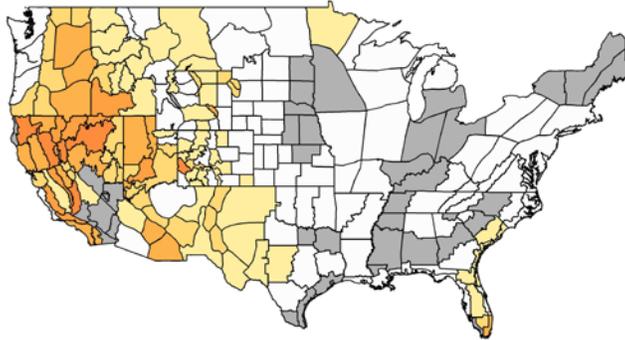


Figure 11. Same as previous figure but at the monthly scale.

a) Historical VLF potential (multi-model mean)



b) Future VLF potential (multi-model mean)

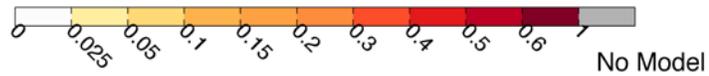
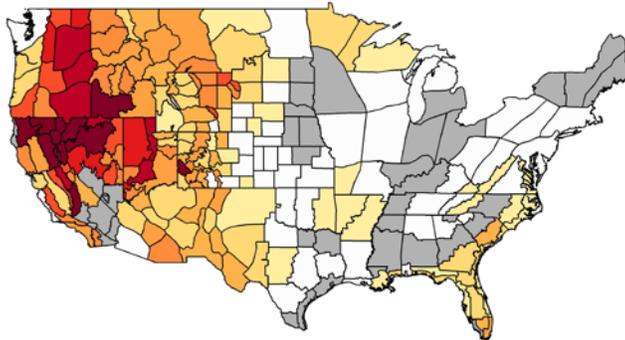


Figure 12. Multi-model mean annual number of VLF weeks per 10,000 square kilometers for historic climate experiment (top, 1971-2000) and mid-21st century climate experiment (bottom, 2041-2070) at the Predictive Service Areas (PSA) level. Gray regions indicate regions with no or insufficient number of VLFs to build robust models.

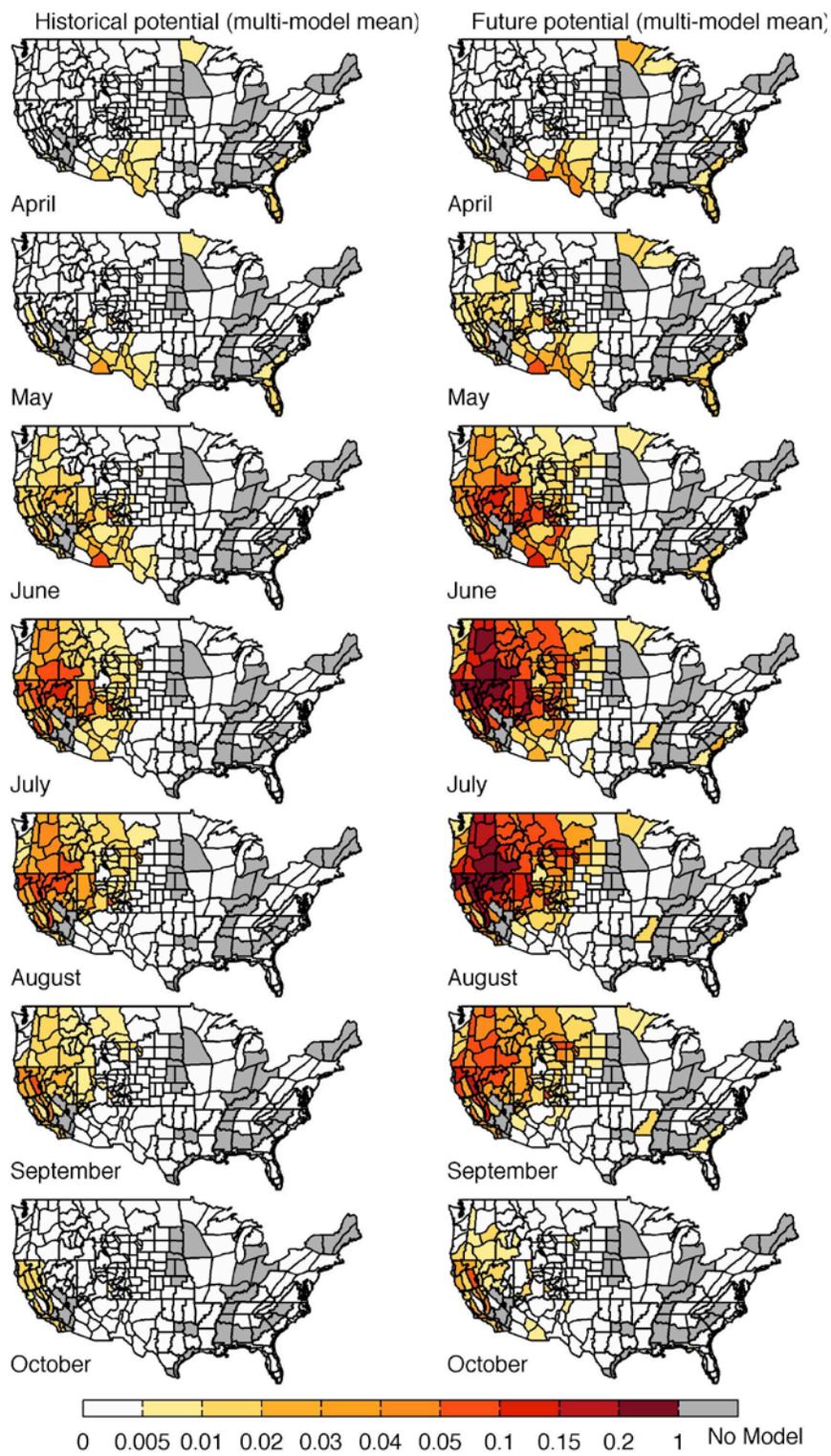


Figure 13. Same as previous figure but at the monthly scale.

- The seasonal window of Very Large Fires is projected to lengthen across many regions of the US.

In many regions there is a substantial advancement in the seasonal onset of VLF potential that will ultimately result in an extension of the VLF season. Unlike the much earlier onset of VLF season in the spring, the models do not project any substantial change in the end of the VLF season in the SW United States associated with the arrival of monsoonal precipitation. Similarly, changes in the seasonality of VLFs are projected for the Everglades (Figure 14).

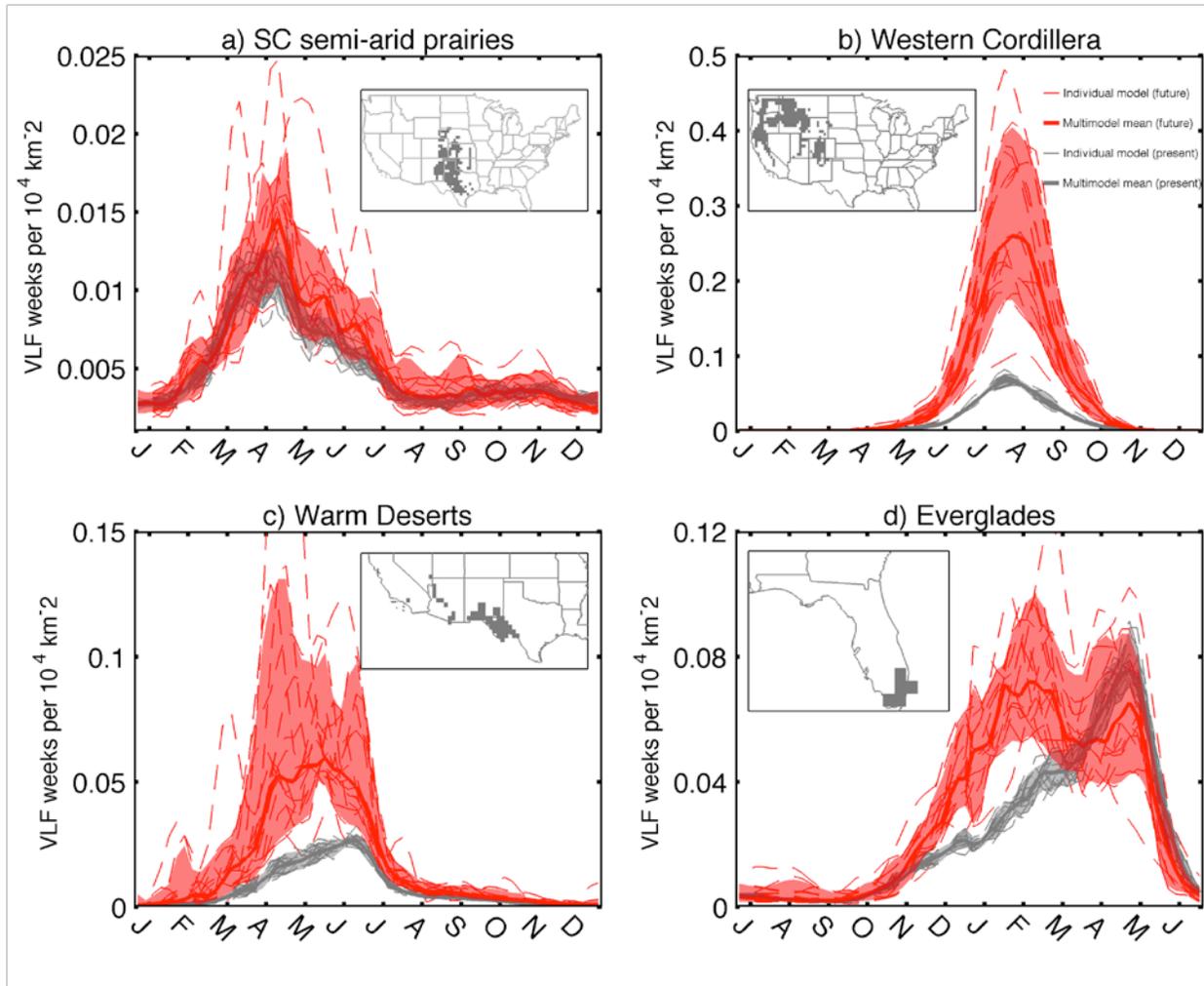


Figure 14. Mean seasonal cycle of VLF potential (P) aggregated to level II ecoregions from 1971-2000 (gray) and 2041-2070 (red). P is expressed as the mean number of VLF expected per surface unit (10^4 km^2) per week. Individual models are shown by dashed curves while the solid bold lines indicate the multi-model mean. Gray and red envelopes indicate the 90% inter-model spread. The insert within each panel indicates the location of ecoregions. Notice that the last panel d) Everglades shows VLF P from July to June.

- **While the magnitude of future mid-century projected change in Very Large Fire potential varies from model to model and scenario to scenario, there is strong agreement of increased Very Large Fire potential for much of the US.**

Substantial inter-model spread in projected changes in mean annual P and weeks of extreme probabilities (conducive to VLFs) are evident; however, nearly all model projections suggest increases above historical level. For example, all models showed an increase in VLF potential in the western Cordillera ecoregion from the baseline historical runs. However, the magnitude of increase projected varies across the GCMs for this ecoregion from an increase of 20% to an increase of more than 400%.

CALCULATING SMOKE IMPACTS

In order to rank potential future very large fire locations on their ability to affect various sensitive receptors – including human populations – we combined two factors: (a) a measure of the typical wildfire emissions emitted per acre at that location (see Appendix H); and (b) the ability of the atmosphere to transport the emissions to the sensitive receptor locations (see Appendix I, J). In addition, for select locations we examined the simple trajectory results against a more intensive full dispersion model (Appendix K). These calculations are described in detail in the Appendices and were done by climatological week. Results are summarized by climatological month and annually.

Figure 15 presents the annual mean Smoke Impact Potential (SIP) for human populations, Class 1 areas, and PM_{2.5} and Ozone non-attainment areas. These maps show the ability for the location shown to impact a specific type of sensitive receptor. As such the value indicated is the SIP for an emissions source at that location (and not the potential for impact at that location).

It is important to note that the SIP is derived on a climatological basis. The transfer functions that relate source and receptor locations (see Appendix I) are not designed to be indicative of where the smoke from a specific fire at a specific time is likely to impact. Instead they are a statistical representation of where, based on past atmospheric transport patterns, it might impact. Thus SIP is only useful in understanding the overall potential for impacts, not in predicting specific impacts.

Human population locations are based on the 2010 census data. Here the SIP is weighted to include the number of people that are within the smoke transport area (see Appendix J). The SIP:Haze version is based on the ability to reach visibility protected Class 1 areas. The SIP:NAAQS_{PM_{2.5}} and SIP:NAAQS_{O₃} versions are based on the ability to reach areas that are currently identified as non-attainment under the National Ambient Air Quality Standards for either PM_{2.5} or Ozone.

- **Smoke Impact Potential is highest along the West coast and across the Midwest.**

Because of the direct dependence of SIP on the location of population centers, along with the generally west-to-east climatological wind direction, SIP is focused along the West coast (where smoke can still affect the large population centers of California, Washington, and Oregon) as well as across major portions of the Midwest including the Ozarks and Appalachians (where smoke can affect significant portions of the eastern seaboard depending on wind direction). Additionally there are high SIP areas west of Denver, and in the upper Minnesota and North Carolina regions (where deep organics can result in high emissions).

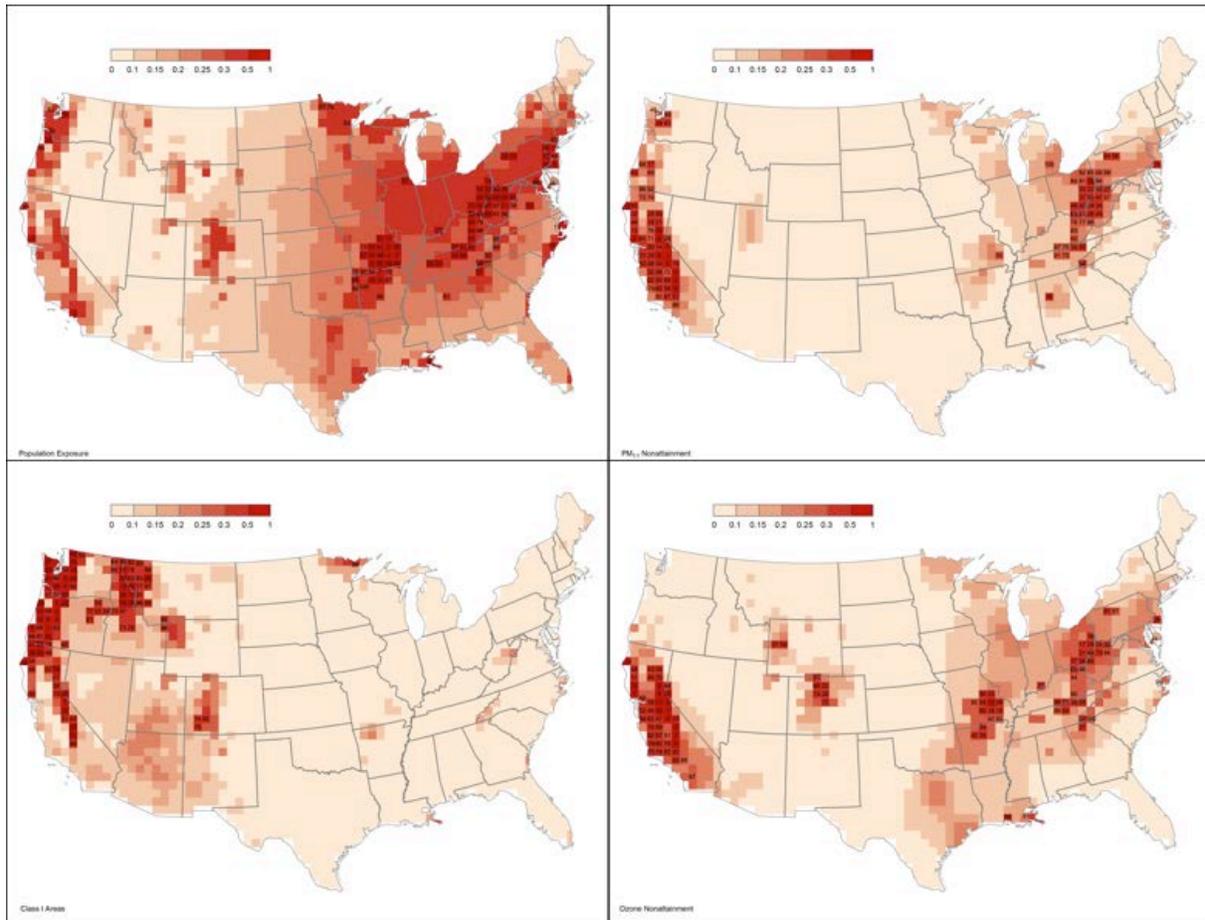


Figure 15. Relative annual Smoke Impact Potential maps with rankings. Upper left: based on population (SIP); lower left: based on Class 1 areas (SIP:Class 1); upper right: based on PM2.5 non-attainment areas (SIP:PM2.5); lower right: based on Ozone non-attainment areas (SIP:O3). Each map is relative to the maximum value for any cell within that map. See text for discussion.

- **Smoke Impact Potential for Class 1 areas and PM2.5 and Ozone non-attainment areas show very different patterns.**

The specific geographic locations of these sensitive receptors result in very different patterns of SIP. Specifically the SIP:Haze patterns are heavily weighted to the northwest – essentially upstream of the locations of the Class 1 area locations. The SIP:NAAQS patterns for both PM2.5 and Ozone are somewhat similar, but with specific locational shifts based on the differences in where the non-attainment regions occur.

4. MANAGEMENT IMPLICATIONS

The results of this work have several implications for fire and land management planning. While these are questions of policy and must be balanced against many factors, the information and results found here have the potential to be useful in helping identify the relative future fire risk of very large wildfires, absent any other management activities. Knowing this risk may allow managers to help prioritize decisions on various mitigation strategies from prescribed burning treatments to road maintenance for fire suppression access. This type of information is also available from other studies (see Appendix G), and combining the results found here with those from other studies using different methods will give managers a better sense of the underlying uncertainties in these types of projections, and where disparate methods agree, greater confidence in these results.

Additionally, this study is the first to link the risk of very large fires to the potential for smoke impacts to population centers as well as to PM2.5 and Ozone exceedences. The resulting rankings can help identify those areas of particular concern from a smoke exposure perspective. Knowing this has the potential to help managers prioritize management actions to mitigate wildfire risk based on the perspective of reducing overall smoke impact risk either regionally or nationally.

Finally, the climatological maps of SIP may have utility for fire management today. Standing alone, these SIP maps are based on historical weather patterns and are not inherently coupled to any future climate projections. They can provide a near-instant assessment of the potential for regional smoke impacts, and could easily be converted into a simple assessment tool of utility for regional area commands or GACCs that want to have a simple system to rank fires based on smoke impact potential.

5. NEXT STEPS

There are many potential next steps that can improve upon the specific models and tools used here. These include:

- Developing a community-wide accepted definition of megafire
- Improving the fire-climate-weather statistical models used to project megafire probabilities
- Specifically examining the likelihood of a large growth day including fire weather connections more directly (this would have to be only on a case study basis due to observational limitations)
- Performing additional analysis on the role of management decisions in the development of megafires, and
- Incorporating these megafire predictions as scenarios in future projections of the full chemistry air model.

In addition to the statistical methodologies used here, we believe that it is useful to examine both the current and future occurrence of very large growth days that seem to be inherent in the ability of fires to become megafires, and in looking at extreme-value theory as an alternative to logistical regression modeling. Both of these efforts are underway as follow-ons to the work presented here.

6. DELIVERABLES

Table 1 presents a crosswalk between the proposed and completed deliverables for this project. This project, in part due to extra work involved in creating the various statistical relationships modeling very large fires, has resulted in significantly more journal papers and conference presentations than originally proposed. Training to management groups, however, is incomplete but is being incorporated into standard trainings and lectures to user groups given by the U.S. Forest Service AirFire Team. In addition, there is an effort to do a webinar through the Northwest Knowledge Consortium.

Table 1. Deliverables Crosswalk

Type	Description	Notes	Status
Datasets	5 datasets proposed covering fire-weather connections to smoke impacts; now complete; 1 modified as below.	Note: back trajectory dataset now smoke transfer functions based on forward trajectories.	Complete
Conference Presentations	2 conference presentations proposed.	11+ conference presentations completed (both oral and posters); more expected.	Complete + 9 extra
Journal articles	2 journal articles proposed.	8 journal articles published so far. Additional manuscripts in progress.	Complete + 6 extra
Training	3 Training Sessions proposed, primarily to smoke groups.	Some training has occurred; additional training currently scheduled. Delayed due to difficulties completing project.	Scheduled
Non-refereed publication	Annual progress reports to the JFSP		Complete
Non-refereed publication	Final Report to the JFSP		Complete

DATASETS

Datasets on very large fire probabilities, emission potential, smoke impact potential were created for this project. All data are available online or by contacting the authors and the metadata are being archived in the U.S. Forest Service Data Archive. See Section 2 for further discussion.

PH.D. THESIS

This work also has resulted in a Ph.D. thesis:

- Stavros, E.N. 2013. *Very large wildfires in the western contiguous United States: probabilistic models for historical and future conditions*. University of Washington, Seattle, Washington. 126pp.

A Master's thesis (H. Podschwit, University of Washington) is currently in progress, based on this work.

EXTENDED ABSTRACTS

- Stavros E.N., Abatzoglou J., Tane Z., Kane V., Veraverbeke S, McGaughey B., Lutz J., Larkin N.K., McKenzie D., Steel E.A., Ramierz C., Boland J., Schimel D. 2014. Regional likelihood of very large wildfires over the 21st century across the western United States: motivation to study explicit events like the Rim Fire, a unique opportunity with unprecedented remote sensing data. *IAWF Proceedings*

CONFERENCE PRESENTATIONS

This is a partial list of oral presentations given as part of this project:

- Stavros E.N., McKenzie D., Larkin N.K., Strand T. October 2011. A stochastic simulation model, Fire-Scenario Builder, to predict daily fire events at regional scales. Ninth Symposium on Fire and Forest Meteorology. Palm Springs, California; oral, presented by Stavros.
- Abatzoglou J.T., Stavros E.N., Larkin N.K., McKenzie D., Steel A. December 2012. A new age of megafires? The role of climate in megafires in the western United States. 5th International Fire Ecology and Management Congress, Portland, Oregon; oral, presented by Abatzoglou.
- Stavros E.N., Abatzoglou J., Larkin N.K., McKenzie D., Steel E.A. April 2013. Megafires: fuel conditions and climate that drive extreme wildfire events in the Western United States. Annual Meeting of International Association of Landscape Ecology (IALE) Conference, Austin, Texas; oral, presented by Stavros.
- Abatzoglou J.T., R. Barbero, S. Larkin, D. McKenzie, E.A. Steel, D. Bachelet, T. Sheehan. 2014. Will climate change increase the occurrence of very large fires in the Northwestern United-States? 5th Annual Pacific Northwest Climate Science Conference, Seattle, USA, 9-10 September 2014, oral, presented by Abatzoglou.
- Podschwit H., Barbero R., Steel E.A., Larkin N.K. December 2014. Building a model to predict megafires using the bagged trees statistical approach. American Geophysical Union Fall Meeting, San Francisco, California; oral, presented by Podschwit.
- Barbero R., J. Abatzoglou, C. Kolden, N.K. Larkin. 2013. The recipe for megafires in Eastern US: the role of the temporal scales. 10th Symposium on Fire and Forest Meteorology, Kentucky, USA, 15-17 October 2013.
- Raffuse S.M., Larkin S., Huang S., Drury S.A., and Lorentz K.A. 2015. Megafires and smoke exposure under future climate scenarios in the contiguous U.S. Presented at the 11th Symposium on Fire and Forest Meteorology, Minneapolis, MN.

This is a partial list of posters presented as part of this project:

- Stavros E.N., Abatzoglou J., Larkin N.K., McKenzie D., Steel E.A. December 2012. Assessing accuracy of a probabilistic model for very large fire in the Rocky Mountains: a High Park Fire case study. Mountain and Climate Research Conference, Estes Park, Colorado; poster, presented by Stavros.
- Stavros E.N., Abatzoglou J., Larkin N.K., McKenzie D., Steel E.A. December 2012. Assessing accuracy of a probabilistic model for very large fire in the Rocky

- Mountains: a High Park Fire case study. American Geophysical Union Fall Union, San Francisco, California; poster, presented by Stavros.
- Abatzoglou J., R. Barbero, B. Stocks, C. Kolden, M. Wotton, S. Larkin. 2014. Atmospheric drivers of daily variations in fire growth of very large wildfires. Large Wildland Fires, Montana, Missoula, USA, 19-23 May 2014; presented by Barbero.
 - Barbero R., J. Abatzoglou, C. Kolden. 2014. Modeling very large-fire occurrences over the continental United States from weather and climate forcing. Large Wildland Fires, Montana, Missoula, USA, 19-23 May 2014; presented by Barbero.
 - Barbero R., J. Abatzoglou, C. Kolden, N.J. Nauslar. 2012. An objective examination of Santa Ana winds events and wildfires in Southern California. 5th International Fire Ecology and Management Congress, Portland, USA, 3-7 December 2012; presented by Barbero
 - Huang S., Larkin N.K., Raffuse S.M., Lorentz K.A., Drury S.A., and Craig K.J. 2014. Megafires and smoke exposure under future climate scenarios in the contiguous United States. AGU Fall Meeting, San Francisco, CA, December 15-19; poster presented by Sonoma Technology, Inc., Petaluma, CA.

JOURNAL ARTICLES

The journal articles published to date from this project are:

- Abatzoglou. J.T., R. Barbero, N.J. Nauslar. 2013. Diagnosing Santa Ana winds in Southern California with synoptic-scale analysis. *Weather and Forecasting*, 28, 704-710.
- Abatzoglou J.T. and Kolden C.A. 2013. Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire*, 22, 1003–1020, doi: 10.1071/WF13019.
- Barbero R., Abatzoglou J.T., Kolden C.A., Hegewisch K.C., Larkin N.K., and Podschwit H. 2014(a). Multi-scalar influence of weather and climate on very large-fires in the Eastern United States. *International Journal of Climatology*, doi: 10.1002/joc.4090.
- Barbero R., Abatzoglou J.T., Steel E.A., and Larkin N.K. 2014(b). Modeling very large-fire occurrences over the continental United States from weather and climate forcing. *Environmental Research Letters*, 9, doi: 10.1088/1748-9326/9/12/124009.
- Barbero, R., Abatzoglou, J.T., Larkin, N.K., Kolden, C.A., and Stocks, B. 2015. Climate change presents increased potential for very large fires in the contiguous United States. *Int. J. Wildland Fire* DOI 10.1071/WF15083.
- Stavros E.N., McKenzie D., and Larkin N. (2014a). The climate-wildfire-air quality system: interactions and feedbacks across spatial and temporal scales. *Wiley Interdisciplinary Reviews: Climate Change*, 5(6), 719-733. doi:10.1002/wcc.303
- Stavros E.N., Abatzoglou J., Larkin N.K., McKenzie D., and Steel E.A. 2014. Climate and very large wildland fires in the contiguous western USA. *International Journal of Wildland Fire*, 23, 899-914, doi: 10.1071/WF13169.

- Stavros, E.N., J. Abatzoglou, D. McKenzie, and N. K. Larkin. 2014. Regional projections of the likelihood of very large wildland fires under a changing climate in the contiguous Western United States. *Climatic Change* 126:455-468.

Links to all of these papers are available on the JFSP page for this project. The list does not include a journal article on the smoke impacts and ranking expected to be published in 2016.

APPENDIX A: DEFINING MEGAFIRES

Ruminations on the difficulty of defining “megafires”

The term “megafire” has been used increasingly over the past decade, primarily in the United States, but also in other countries, to generally describe more frequently occurring large, high-impact wildland fires. However, a definition of a “megafire” that includes agreed-upon characteristics, has yet to be crafted by the wildland fire management community. In fact, a universally acceptable definition is likely not possible.

The “megafire” debate has been driven by the argument that the number and intensity of wildland fires is increasing, and that impacts are growing alarmingly. There is a consensus that a combination of climate change-driven droughts and lengthening fire seasons, an over-accumulation of fuels in fire-dependent ecosystems due to effective suppression in recent decades, and the rapid expansion of high-value wildland-urban interface areas is responsible for increasing fire impacts. Wildfire costs are increasing dramatically, but having little influence as fire and smoke impacts on life and property are becoming more frequent and extensive, and this trend can be expected to continue as climate change escalates.

However, there is no consensus that a term such as “megafire” is required to address the changes underway in fire behavior and impacts. Many argue that these wildfires are not fundamentally different than wildfires of the past, but that they represent a change in frequency and scale - occurring more often and at higher intensities, making control much more challenging. Despite these disagreements on terminology, there is strong agreement that fire activity and impacts are increasing, and that a more effective land management model will be required to help mitigate this problem (Williams, 2013).

Recent US fire statistics indicate that 95% of all fires are suppressed at initial attack, while another 4% escape initial attack and become extended attack operations, but are generally suppressed in a short period of time. The remaining 1% of wildfires are complex incidents that require the management and oversight of an organized Incident Management Team (IMT). Within this 1%, only a few fires become “megafires,” due to a combination of size, complexity and resistance to control (Brookings, 2005).

Figure A-1 shows the number of large fires and their contribution to area burned post 1984, using data obtained from the Monitoring Trends in Burn Severity (MTBS) database. The number of large fires has increased substantially over this period, accounting for a disproportionately high percentage of total suppression costs, private property losses, resource damages, and area burned.

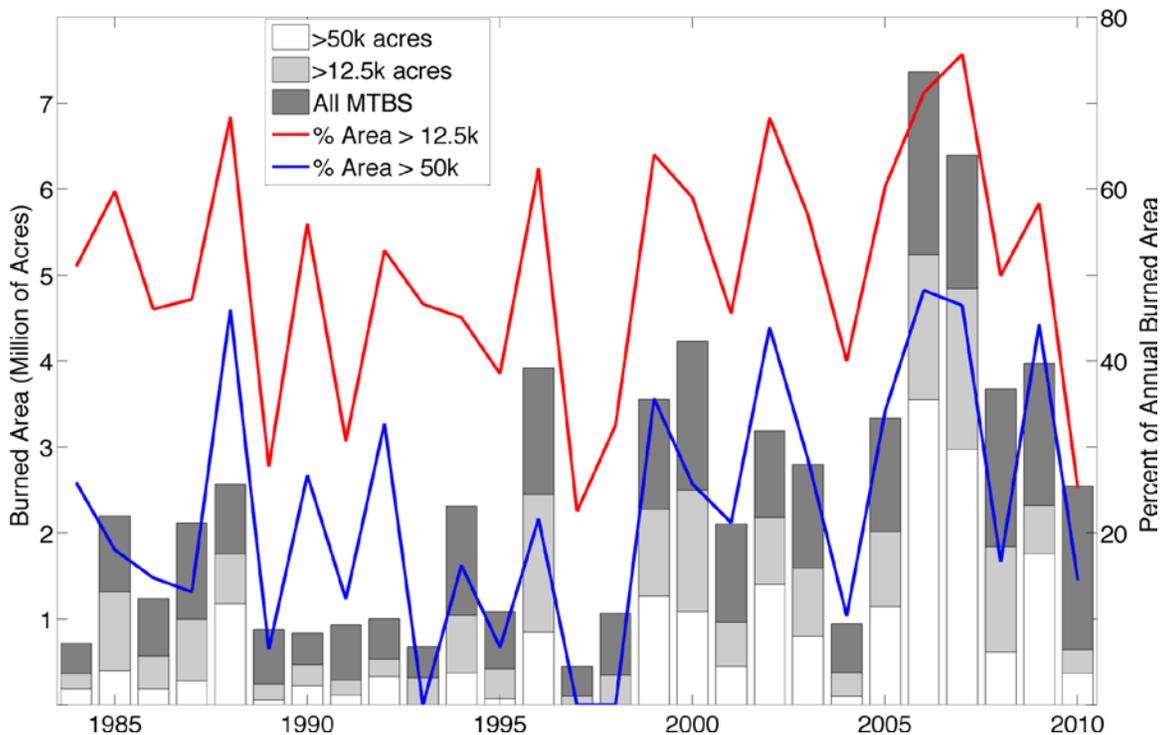


Figure A-1. Annual burned area for the contiguous United States from MTBS fires from 1984-2010 for all fires, VLF exceeding 12,500 and 50,000 acres. The red and blue lines show the percentage of annual burned area in VLF exceeding 12,500 acres and 50,000 acres, respectively.

In this analysis we refer to these high-impact “megafires” as Very Large Fires (VLFs) and restrict our analysis of fires above a particular threshold acres in size. As mentioned, fire size is not the only criteria in measuring fire impacts, but it was felt that fire size is easier to relate to fire weather and danger than other fire metrics such as costs, suppression effort and infrastructure impacts. At various stages of the project we used both > 50,000 acres and > 12,500 acres in our analyses (see sections below for specific details).

APPENDIX B: BEHAVIOR AND IMPACT OF SELECTED 'MEGAFIRES'

A case-study examination of 'Megafire' commonalities and differences

In order to better understand why the number and impact of VLF in the United States has been growing rapidly in recent years, it was felt that a closer examination of a number of major fires larger than 50,000 acres would be informative, and may identify some of the reasons why particular fires grow larger than others that escape initial attack. Fire size is not the only measure of fire impacts; overall costs, community destruction, infrastructure loss, environmental degradation, suppression air quality, and human health concerns are also important. However, fire size is a more easily-quantified impact that can be related directly to fire weather and fire danger conditions. These relationships could then be used with projected future climates to predict future fire impacts.

A total of 21 recent (2002-2013) VLFs were selected for a detailed analysis of fire growth, with 20 of these fires occurring in the western contiguous United States (CONUS) and the remaining fire in Minnesota. All of these fires were well-known major events with significant impacts and media attention that created awareness that large fire activity was increasing, particularly in the western US. These fires are listed in Table B-1, along with various fire characteristics such as date, cause, location, fuels, duration, final size, and total suppression expenditures. They occurred in a variety of forested, rangeland and chaparral ecosystems, and ranged from very high-impact wildland-urban interface fires to wilderness fires. Some fires were of short duration, while others grew steadily over extended periods. Burning periods (the number of days from ignition to when a fire reached 98% of the final fire size) ranged from 4 to 55 days. All fires were large (>50,000 acres), with final sizes ranging from ~92,000 to over 500,000 acres. Suppression costs for these fires also varied highly, from a low of \$4.5 million to a high of \$200 million (2014 US dollars, adjusted for inflation). Collectively, total suppression costs for these fires amounted to over \$1.3 billion.

Daily fire growth information for each fire was obtained from the historical archive of incident status summary (SIT-209) reports http://fam.nwcg.gov/fam-web/hist_209/report_list_209 grouped by Geographic Area Coordination Centers (GACCs). Cumulative daily fire growth for these fires is summarized in Figure B-1.

Table B-1. Summary information for 21 VLFs. Burning days = ignition date to date of 98% of final area burned; Cause = lightning (L) or human (H); Cost = suppression costs in thousands of dollars, adjusted for inflation to 2014.

Fire	State	Year	Start date	Size (ac)	Burning Days	Cause	Major Fuels	Cost (1,000s)	Cost/acre	Fatalities	Struct-ures lost
Ash Creek	MT	2012	25-Jun	249,562	12	L	timber, grass	\$7,733	\$31	0	39
Basin Complex	CA	2008	23-Jun	162,818	34	L	chaparral, timber	\$85,870	\$527	0	58
Biscuit	OR	2002	13-Jul	499,000	40	L	mixed conifer, brush	\$200,887	\$403	0	13
Cedar	CA	2003	25-Oct	280,278	6	H	chaparral, brush	\$41,964	\$150	15	2,820
Day	CA	2006	4-Sep	162,700	26	H	chaparral	\$91,594	\$563	0	11
Hayman	CO	2002	8-Jun	138,114	10	H	mixed conifer	\$51,584	\$373	0	618
Las Conchas	NM	2011	26-Jun	156,593	21	H	mixed conifer, juniper	\$50,922	\$325	0	112
Long Butte	ID	2010	21-Aug	306,113	4	L	brush, grass	\$4,587	\$15	0	12
Milford Flat	UT	2007	6-Jul	363,052	7	L	brush, grass	\$5,763	\$16	0	2
Miller Homestead	OR	2012	8-Jul	160,853	8	L	brush, grass	\$6,187	\$38	0	3
Mustang Complex	ID	2012	30-Jul	341,448	55	L	timber	\$39,515	\$116	0	7
Pagami Creek	MN	2011	18-Aug	92,682	29	L	timber	\$23,891	\$258	0	2
Rim	CA	2013	17-Aug	257,000	22	H	brush, oak/pine	\$129,416	\$504	0	112
Rodeo-Chediski	AZ	2002	18-Jun	468,638	13	H	chaparral, pine, juniper	\$19,963	\$43	0	423
Rush	CA	2012	12-Aug	315,567	10	L	grass, brush	\$50,254	\$159	0	1

Station	CA	2009	26-Aug	160,557	14	H	chaparral	\$105,393	\$656	2	209
Tripod Complex	WA	2006	24-Jul	175,184	49	L	timber	\$97,319	\$556	0	2
Wallow	AZ	2011	29-May	538,049	24	H	timber, grass	\$114,717	\$213	0	72
West Fork Complex	CO	2013	5-Jun	109,615	25	L	timber	\$31,768	\$290	0	1
Witch Creek	CA	2007	21-Oct	197,990	4	H	grass, brush	\$20,552	\$104	2	1,634
Zaca	CA	2007	4-Jul	240,207	52	H	chaparral	\$139,561	\$581	0	1

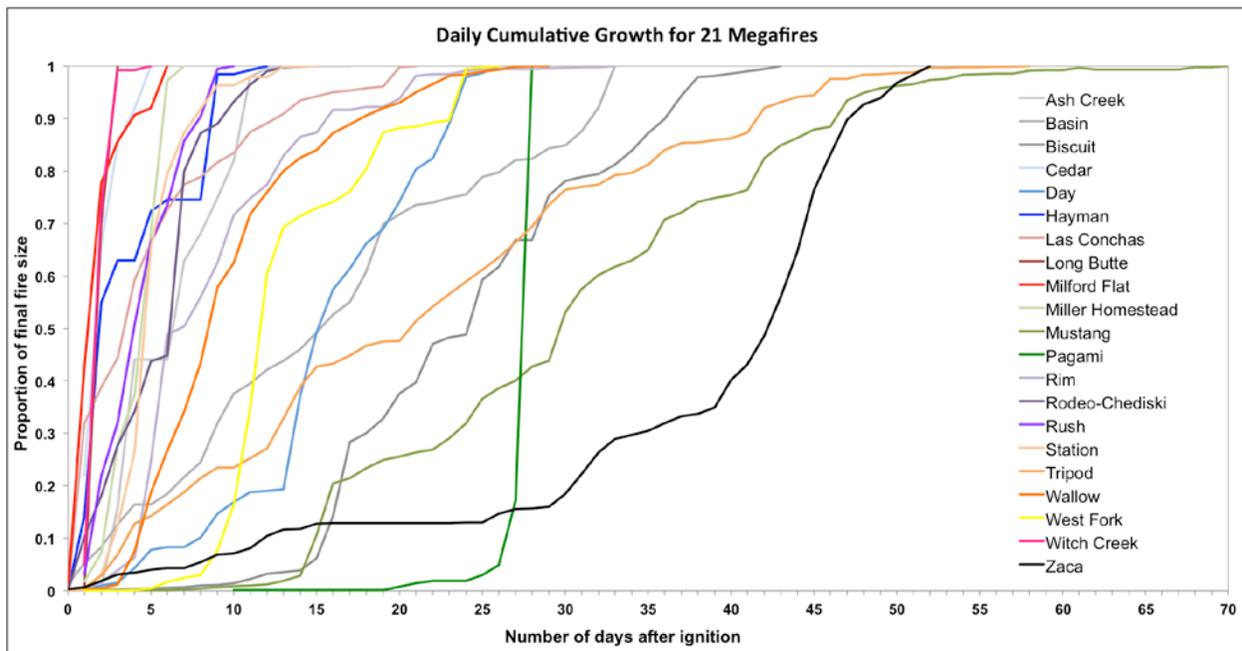


Figure B-1. Daily cumulative growth (as a proportion of final fire size) for 21 VLFs.

The fires shown in Figure B-1 fall into two distinct groups: a larger group of those that grew very quickly in the first week and the remainder that grew more slowly, while still presenting control difficulties. In general, the faster-burning and shorter-lived fires burned in lighter fuels (e.g., brush, grass), while the longer-burning fires were usually in timber. The longest-burning fires also tended to be in more remote regions, although several of the relatively short fires were also in more remote areas (particularly the Great Basin).

Using a larger sample of daily fire growth derived from the SmartFirev2 data that included all MTBS fires from 2003-2010, we found that fires whose total burned area exceeded 20,000 (20k) acres generally burned over a longer duration than fires that burned less than 20k acres. The median duration, herein defined as the number of days from discovery to when at least 95% of the total burned area occurred, was 15.7 days for fires > 20k acres, and 3.3 days for fires < 20k acres. Moreover, half of all very large fires (>20k acres) burned 50% and 90% of the final burned area within 4 and 14 days post discovery, respectively. This compared to half of all other MTBS fires (<20k acres) that burn a 50% and 90% of the burned area on the date of discovery and within 5 days post discovery, respectively.

We analyzed daily growth as a function of fire weather and fire danger conditions, particularly during the early phases of fires after they escape initial attack and begin to grow large, as this is a critical tipping point in terms of early and effective control. There are many other factors that could affect growth during this critical period, including fuels, topography, accessibility, resource availability, local to regional to national fire load etc., but this analysis is constrained to fire danger conditions.

Daily fire growth information from SIT-209 reports was compiled for the duration of each fire. These summary reports are generally issued in the evening and capture fire growth during the peak afternoon burning period. Fire weather and fire danger data from nearby weather stations was obtained from the Fire Family Plus website <http://fam.nwcg.gov/fam-web/weatherfirecd/>. Modeled fire weather/danger data were also obtained from the gridded surface meteorological dataset of Abatzoglou (2013). We extracted data for the 4-km voxel closest to each the fire centroid, assuming that meteorological conditions were temporally common across the fire perimeter.

Fire danger variables from both the United States National Fire Danger Rating System (Bradshaw et al., 1983) and the Canadian Forest Fire Weather Index (FWI) System (Van Wagner, 1987) were compared with daily fire growth. These included the Energy Release Component (ERC) and Burning Index (BI) from the US system using fuel model G and the Fire Weather Index (FWI) and the Initial Spread Index (ISI) from the Canadian system. These indices were selected as the best indicators of fire spread and intensity, thereby being most likely to reflect fire behavior levels that would challenge initial attack success and relate well with fire growth.

Initial results, relating daily growth rates and fire danger over the active burning period for each fire and collectively, did not show any strong correlation. Since daily growth rates would be affected to some degree by suppression efforts, even under significant fire danger conditions, and this would be most prevalent during the latter stages of a large fire, a further analysis was conducted using data from the period during which the fire grew to half of its final size. This would be a period when suppression efforts would be less effective, with the fire spreading more naturally, although other factors (e.g., fuel type and continuity, topography etc.) would still exert an influence. This generally improved correlations somewhat, but they were still not significant. This is not completely surprising as daily growth is not the same as spread rate, and is greatly affected by the length of existing fire perimeter. The first day of the fire was also excluded from this analysis, as the growing period on this day varies depending on the time of ignition.

While no strong correlations between any of the indices and fire growth were evident, all fires in Table B-1 burned under extreme fire danger conditions (above 95% levels for ERC, BI, FWI and ISI) that were sustained throughout much of the fire period, indicating that effective fire control would be challenging. These fires all grew substantially on the day of ignition and escaped initial attack, making further substantial growth on subsequent days possible. As typical examples, fire danger levels on the Wallow and Rodeo-Chedeski fires are shown in Figures B-2 and B-3. ERC FWI, BI and ISI values are all well above normal both before and during these fires. This was generally true on all of the selected 21 fires in this analysis.

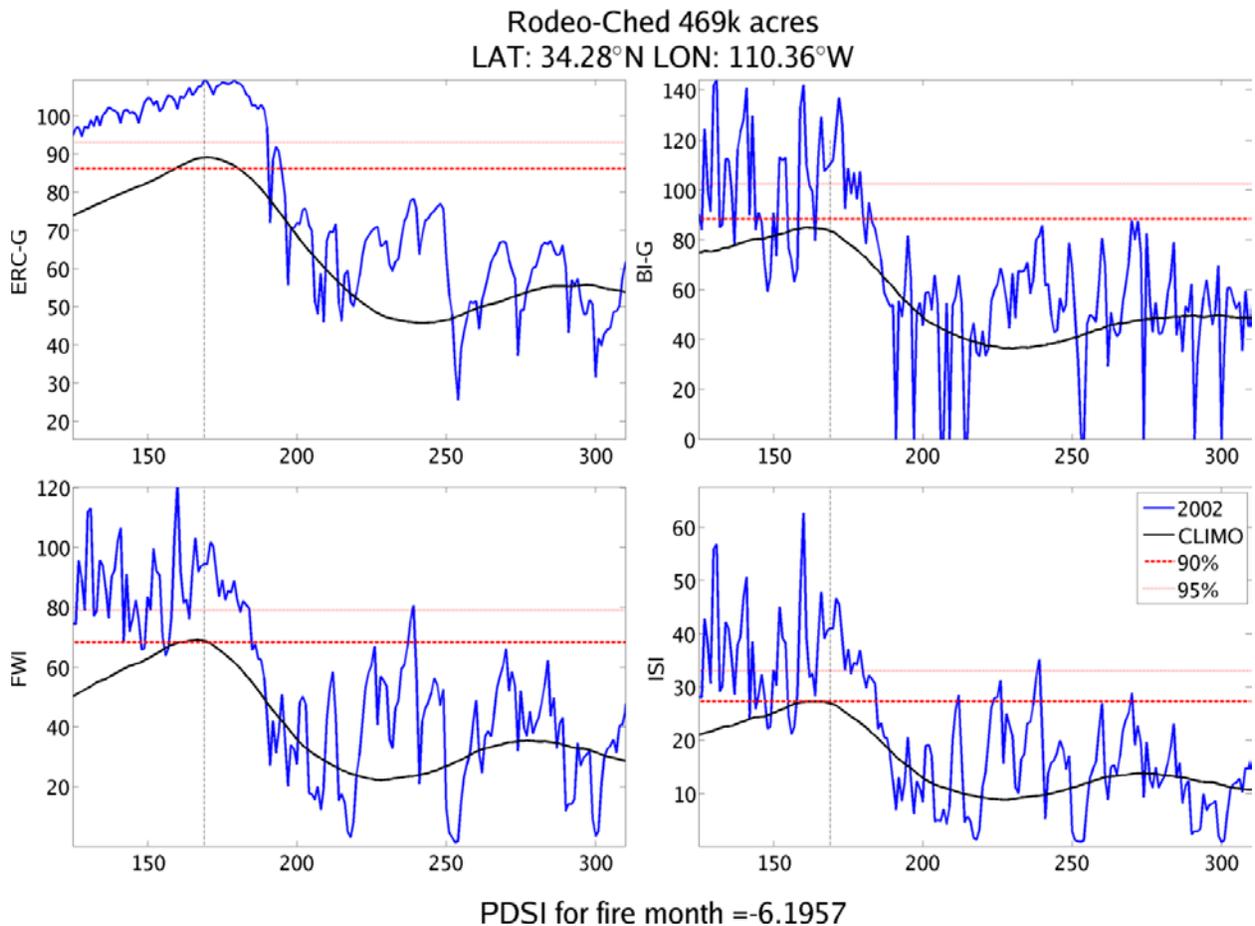


Figure B-2. Observed daily fire danger indices Energy Release Component (ERC, fuel model G), Burning Index (BI), Fire Weather Index (FWI) and Initial Spread Index (ISI) calculated from 4-km gridded weather data at the fire centroid for the Rodeo-Chedeski fire. The Palmer Drought Severity Index (PDSI) for the month concurrent with the fire start date is shown below. The x-axis represents the day of year. The dashed vertical line denotes the discovery date of the fire, and the two dashed horizontal lines show the 90th and 95th percentile values calculated using the entire period of record. For reference, the smooth black line shows the moving 21-day climatology calculated for the period of record.

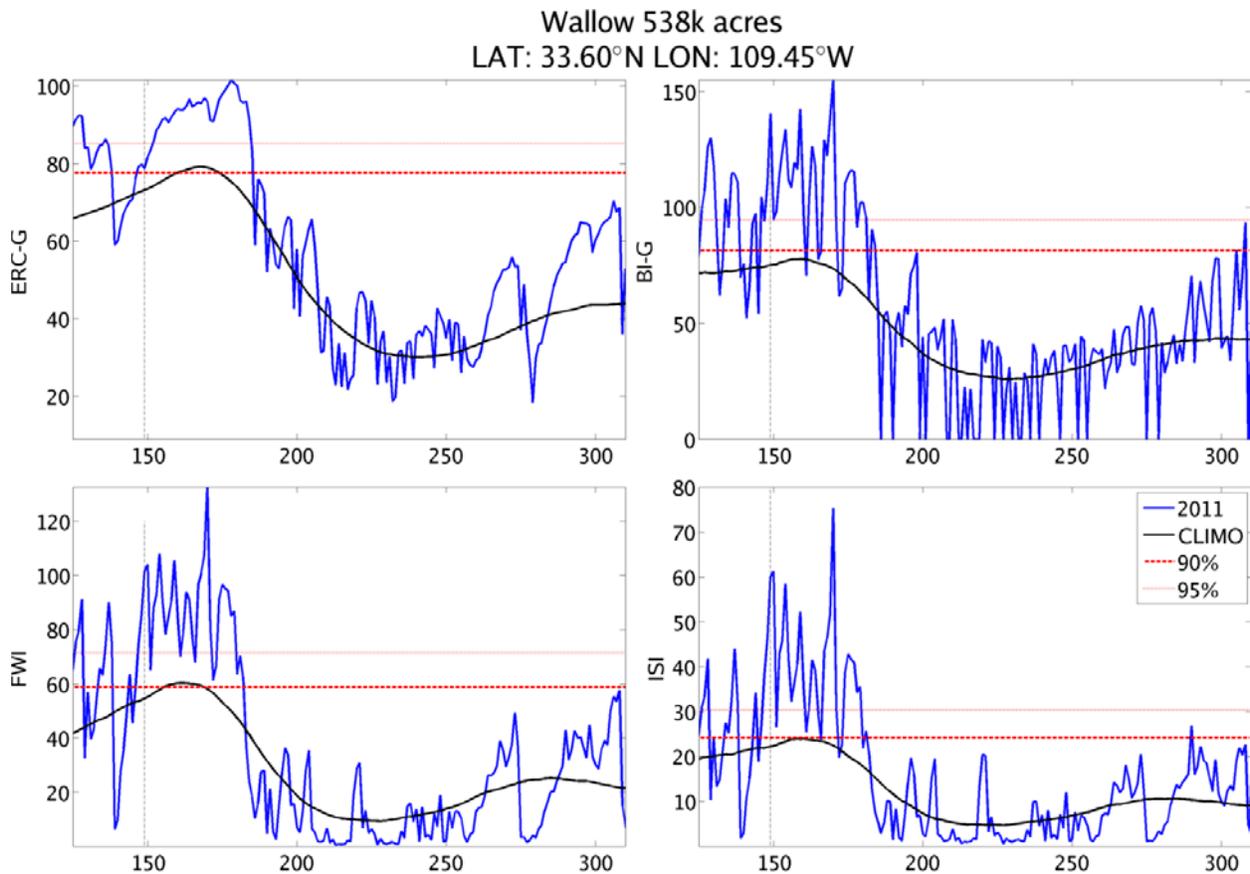


Figure B-3. As in Figure B-2 but for the Wallow fire.

Despite the fact that daily fire growth during the most active periods on these fires was not strongly correlated with fire danger, it is undoubtedly true that extreme fire danger conditions before and during these VLFs undoubtedly contributed to them escaping initial attack and subsequently growing large. This raises the question whether this is a more noticeable effect on the VLFs >50,000 acres in our study in comparison to smaller fires that also escape initial attack. To further address this question, we grouped fires from the MTBS database into three size classes (5000-20000 acres, 20000-50000 acres, and >50000 acres) and investigated the ERC, FWI and BI conditions under which they occurred.

Significant differences in the behavior of fire danger indices following the discovery date were observed across fire size classes. Fires that burned between 5,000 and 20,000 acres generally occurred under less extreme fire danger conditions concurrent with the discovery date and well after the discovery date (Figure B-4). Relatively minor differences were noted between fires that burned between 20,000 and 50,000 acres and those that burned more than 50,000 acres beyond a week after the discovery date. Fire danger indices were significantly higher for the 5-7 days post discovery for fires that eventually burned 50,000 acres or more.

However, when conducting a similar analysis at a regional-scale the results can be somewhat different. For example, we found significant differences in ERC 3-5 weeks following discovery

dates for fires greater than 50,000 acres versus smaller fire size classes for a subregion of the Northern Rockies covering 4 Predictive Service Areas from the Idaho panhandle, northwestern Montana and Glacier National Park (Figure B-4). In these forested ecosystems, prolonged ERC values near the 95th percentile for a full month following fire discovery allow for active fire and may limit suppression.

Daily and total fire suppression costs were also obtained from the SIT-209 forms and adjusted for inflation to 2014 equivalent based on adjustment factors from the Bureau of Labor Statistics Consumer Price Index calculator. These numbers represent only actual suppression costs, and do not include costs associated with fire-caused damages. Suppression costs are a function of multiple factors, and we normalized costs across fires through two approaches. We normalized cost by area burned, deriving a cost/acre value for each fire. While total suppression costs are often accumulated for much longer than the number of burning days due to long-term mop-up and rehabilitation efforts that extend well beyond the date of fire containment (Figure B-5), the latter dates (both containment date and final cost incursion date) are often less reliable in the records, and can be controlled by factors such as when the first snowfall occurs, effectively ending fire season. This difference is obvious in examining examples from the Rim Fire, where containment and the end of suppression cost accumulation were essentially concurrent due to a season-ending event, and the West Fork Complex, where suppression costs continued well beyond the primary burning period due to the fire being in complex wilderness terrain (Figure B-6). Thus, the number of burning days was more consistent to calculate across fires.

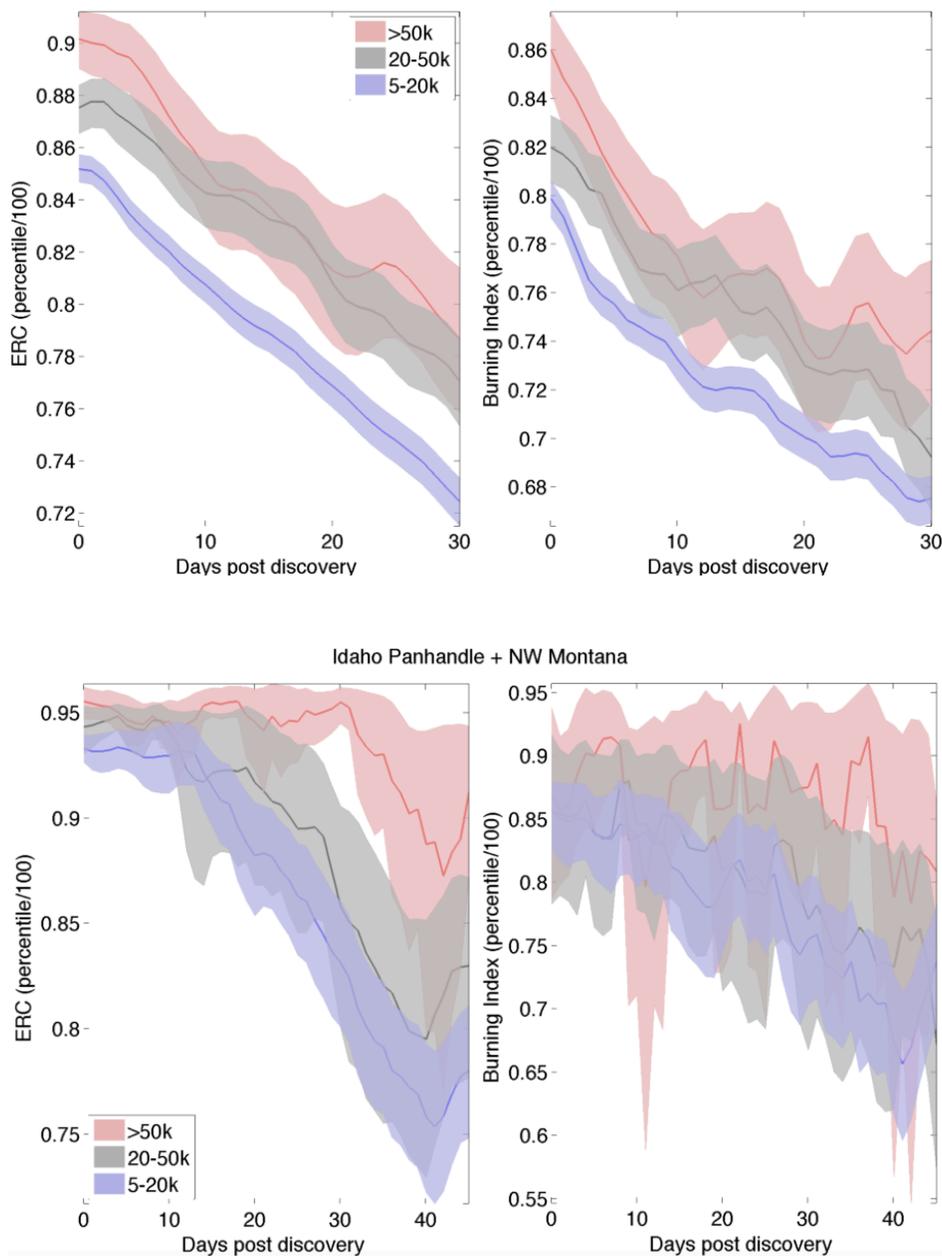


Figure B-4. Top panels: Composite (left) daily ERC and (right) BI converted to local percentiles for all MTBS fires in CONUS that reached a final size of 5,000 to 20,000 acres (blue), 20-50,000 acres (grey) and more than 50,000 acres (red). The shading denotes the 95% confidence interval of each composite assessed using bootstrap analysis. Bottom panels: Same as top, but for four predictive service areas in northern Idaho and western Montana (Southern Panhandle Idaho/Western Montana, North Central Idaho/Southwest Montana, Glacier National Park/Wilderness, and Northern Panhandle Idaho/Northwest Montana).

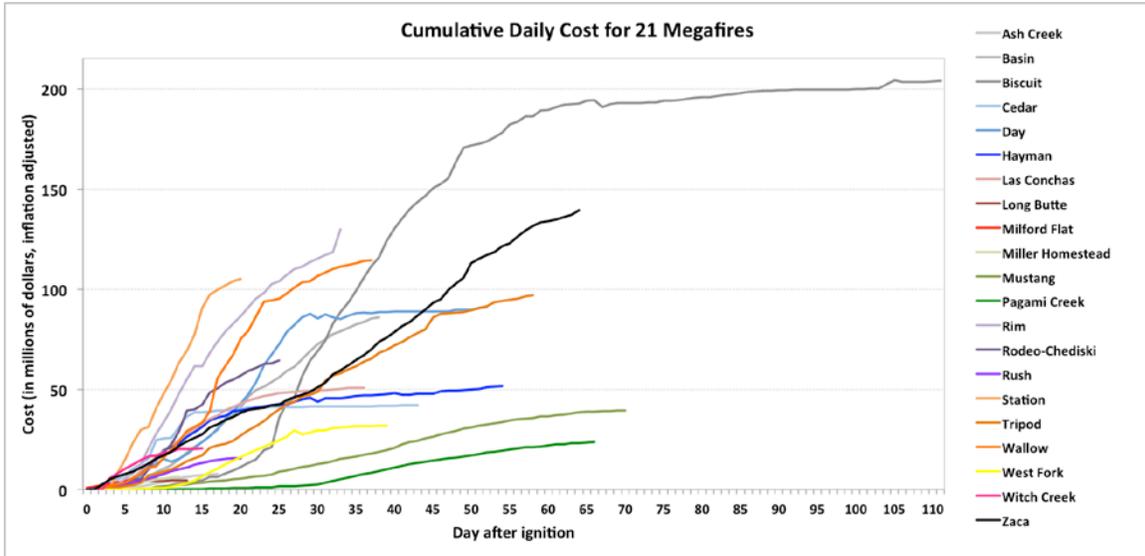


Figure B-5. Cumulative suppression costs in millions of dollars (adjusted for inflation) for 21 VLFs by the number of days after fire ignition (Day 0).

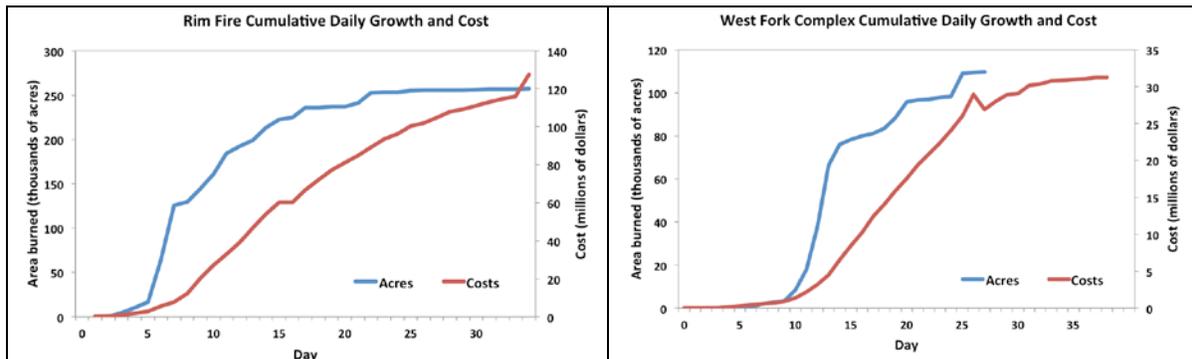


Figure B-6. Cumulative growth curves for the Rim Fire (left) and the West Fork Complex (right) showing the daily progression of fire growth in thousands of acres (blue lines) and the daily accumulation of fire suppression costs (red lines). Day 0 indicates ignition date.

While longer fires and larger fires were generally associated with greater suppression costs (Figure B-7), these relationships were relatively weak. When we normalized costs per acre and per burning day, relationships improved slightly, but were still weak. However, in normalizing the fire costs by area and then visualizing this cost/acre against the number of burning days, patterns begin to emerge concerning fire costs (Figure B-8).

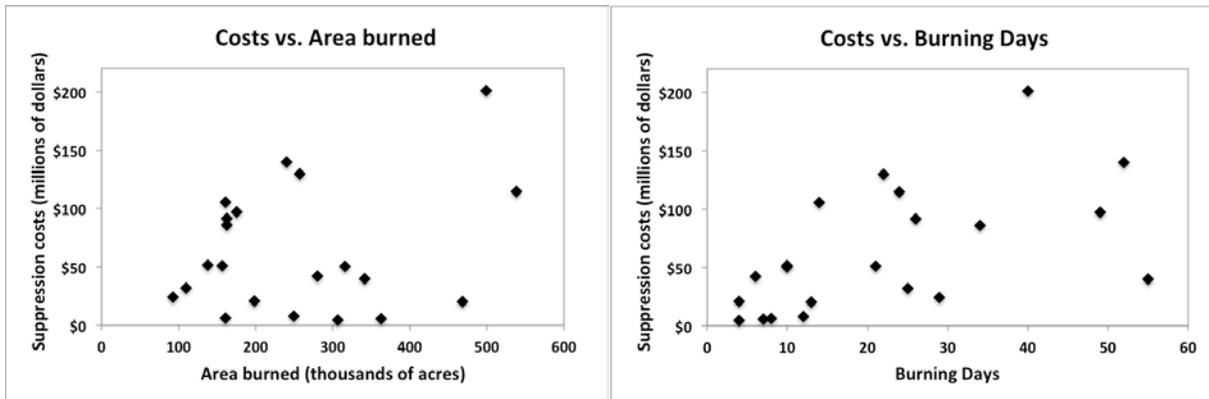


Figure B-7. Relationships between suppression costs (millions of dollars, adjusted for inflation) and both area burned (thousands of acres; top) and number of burning days to 98% of final fire size (bottom) for 21 VLFs.

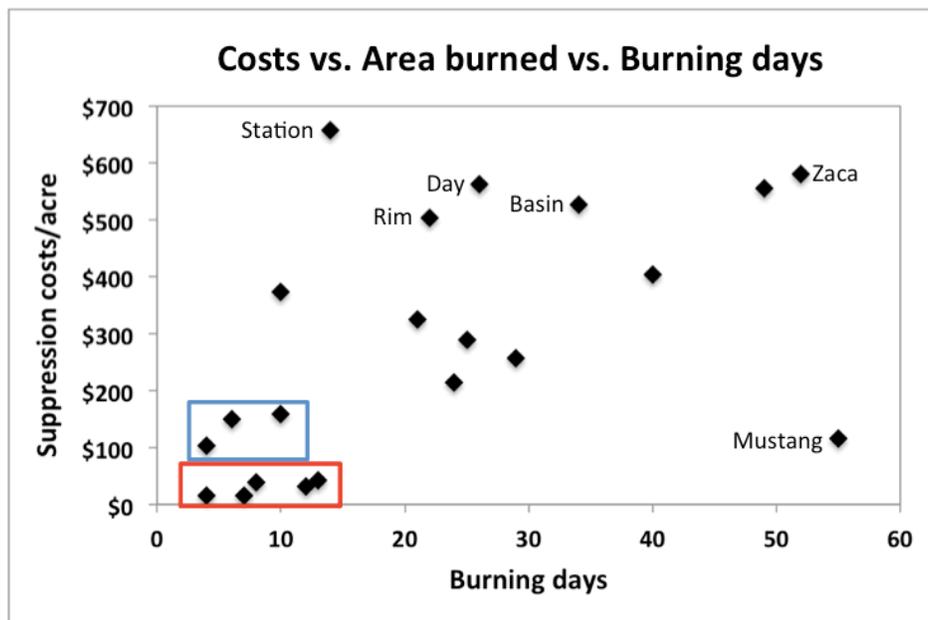


Figure B-8. Suppression costs per acre burned versus number of burning days for 21 VLFs. Fires in red box were relatively short duration fires outside of California (i.e., Ash Creek, Long Butte, Milford Flat, Miller Homestead, and Rodeo-Chediski). Blue box includes short duration fires in California (i.e., Cedar, Rush, Witch Creek)

There are two clear distinctions in this visualization. First, the short duration and relatively low cost fires (8 total) were primarily burning in lighter, flashier fuels such as grass (or grass under a timber overstory) and shrubs, while the longer duration and higher cost fires were primarily burning in heavy shrubs and timber (13 total fires). Second, for both of these groups (shorter/lower cost vs. longer/higher cost), the fires in California were overwhelmingly more expensive to suppress than fires outside of California (Figure B-9).

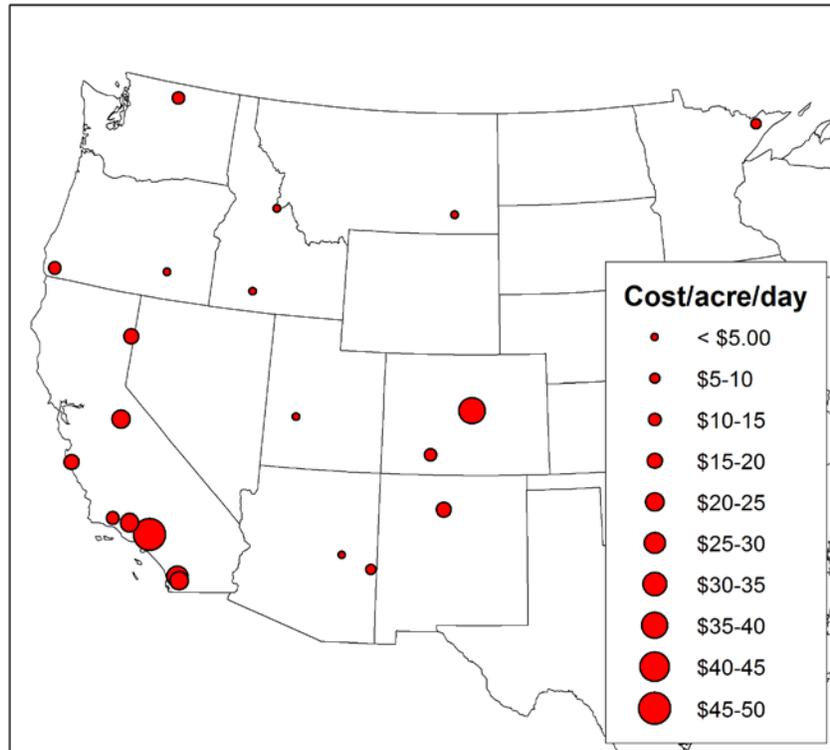


Figure B-9. Map of 21 VLFs, where dot size represents suppression costs per acre burned per burning day.

While some of the literature on fire expenditures argues that this is associated with the complex wildland urban interface (WUI) found across much of California, several of the California VLFs did not burn in areas with extensive WUI concerns. For example, both the Rush and Basin Complex fires occurred in more remote areas: the Rush Fire in the very northeastern corner of the state, and the Basin Complex in wilderness along the central coast south of Monterey. However, both of these fires still had higher suppression expenditures per acre than comparable fires not within California. This discrepancy points to a different approach to fire suppression in California versus outside the state, and is further illuminated by examining the two points on the cloud which occur at opposite ends of the expenditure spectrum: the Mustang Fire in Idaho, and the Station Fire in California. Despite its large size and long burning period, the Mustang Fire had relatively low suppression costs per acre burned. This was in part due to its location in a wilderness area in central Idaho that has a long history of utilizing prescribed natural fire, wildland fire use, and fire for resource benefits. The Mustang Fire was initially managed as such, and suppression efforts were only selectively applied as the eastern flank of the fire approached a major US highway and several small towns. The remainder of the fire was monitored but left largely unstaffed due to inaccessible terrain, safety concerns, and low probability of successful suppression.

By contrast, the Station Fire was the most expensive VLF to suppress on a cost/acre basis. While the fire began in the Wildland-Urban Interface (WUI) on the edge of the Los Angeles basin, it ultimately moved into less-accessible terrain in the Angeles National Forest. Costs were driven by three primary factors: 1) an extensive use of aerial suppression resources because of the

political ramifications of being a high-visibility fire (the plume could be easily seen by millions of people around the LA basin); 2) a joint command with CALFIRE, resulting in extensive use of more expensive state and municipal fire suppression resources (as compared to US Forest Service resources); and 3) the use of more indirect attack tactics following two firefighter fatalities during the early part of the fire. While most large wildfires around the LA basin are associated with autumn Santa Ana wind events, the Station Fire did not occur under a high wind scenario and was predominantly driven by complex topography and heavy fuels.

Overall, examining the daily SIT reports for costs of suppression, fire growth, number of personnel assigned to the fire, number of days as national fire priority for resources, and the type of incident management team assigned to manage the fire help to delineate the 21 VLFs examined in the case study into three key categories: wind-driven, remote fuel-driven, and WUI fuel-driven. Wind-driven fires are generally short-lived and associated with either Santa Ana events (in California) or other multi-day events characterized by winds >50 mph that carry the flaming front rapidly through grass or shrub fuels. These fires generally do not lack for suppression resources or effort to suppress; fire behavior is simply too extreme to successfully suppress until the wind dies down. They are the cheapest fires overall because of their very short duration, although California wind-driven fires are more resource-intensive, more expensive to suppress, and generally consume more structures than non-California wind-driven fires, which are more often in remote locations. Because their rapid expansion requires road closures and mass evacuations, and because they are often associated with a high rate of structure loss, these are high-impact VLFs.

Fuel-driven fires in WUI areas are also characterized by high suppression costs, both due to the greater number of state and municipal fire engines that are assigned to structure protection and due to the more extensive aerial resource support associated with saving homes. These VLFs tend to be high impact due to structure threats and losses, and also due to the negative smoke and air quality impacts they have on urban and semi-urban areas. The climatological analysis shows that many of these fires occur under extreme or even record fire weather conditions. This combination of extreme weather and a WUI fuel mosaic can produce a high-impact VLF.

Fuel-driven fires in more remote areas are primarily considered high-impact VLFs primarily based on size, although some of these fires are considered high impact because they consume high-value commercial timber or threaten the integrity of critical watersheds that feed urban water supplies. Remote fuel-driven VLFs tend to be characterized by several common denominators: 1) they are often difficult to access because many of them start in wilderness areas (making early containment nearly impossible when desired); 2) they exhibit extreme fire behavior associated with record drought and/or fire weather conditions; 3) they burn in fuels that are fundamentally altered from the historical state, such as high-density forests where fire has been repeatedly suppressed or extensive stands that have been killed by insect outbreaks; and 4) suppression efforts more commonly include a mix of indirect attack, large burnout operations, unstaffed segments of the fire, and fire for resource benefits in order to maximize firefighter safety, minimize suppression costs, and meet ecological restoration objectives. The Mustang Complex, Pagami Creek, and West Fork Complex fires were all initially managed for resource benefits; extensive suppression only began when the fires grew large enough outside the wilderness areas where they ignited to begin threatening residences and critical infrastructure

resources. The extended no-suppression burning period reduced overall suppression costs on these fires, particularly relative to the number of burning days, as evidenced in Figure B-5. In all three of these fires, they primarily required heavy suppression resources only for a short period of critical fire weather, keeping overall suppression costs low.

In summary, a case study of 21 VLFs reveals that a variety of factors contribute to the high level of impact associated with these fires. While VLFs more broadly across the US have been characterized as the product of fire climatology and extreme fire weather conditions (i.e., physical drivers), the case study reveals that human factors also contribute to impacts and help determine what are considered VLFs. Whether fires occur in ever-expanding WUI areas or not is a factor for final suppression costs and potential for structure loss, and, if fires occur in California, they are likely to have higher suppression costs associated with the suppression hierarchies and comparatively heavy utilization of state, municipal, and aerial firefighting resources in that state. Past land management influences potential for VLFs, with past suppression and logging history altering historical fuel loading. VLFs that are managed for a complex outcome, such as a mix of suppression and non-containment for resource benefits, may still grow large in size, but the costs to suppress them are comparatively lower than fires of a similar size and duration that undergo full suppression. Ultimately, the diversity of both impacts and contributing factors suggests that VLFs will not be easy to predict in the future based solely on climate model outputs, but also that a size-based definition of VLFs will not capture the diversity of long-term benefits and consequences.

Summary Points

- The project analyzed 21 high-impact VLFs (>50000 acres) between 2002 and 2013.
- There was a large variation in final sizes and suppression costs.
- All fires escaped initial attack and grew quickly.
- Growth rates varied between fires.
- Fuels ranged from grass and brush to chaparral and forests.
- Extreme fire danger conditions prevailed before and during all fires.
- No strong correlation between daily fire growth and fire danger conditions, likely due to many other factors at play.
- VLFs >50,000 acres in size appear to have burned over a longer period of extreme fire danger than smaller fires that also escaped initial attack.
- Fire suppression costs, and the rate at which they accumulate, can be quite variable among fires.
- Fires can be primarily grouped into three groups: wind-driven intensive, WUI fuel-driven, and remote fuel-driven.
- Size-based definition does not fully capture diversity of human and environmental factors contributing to VLFs.

APPENDIX C:

SCALE AND STATISTICAL CONSIDERATIONS IN STUDYING VERY LARGE FIRE OCCURRENCES

Wildfire is a complex phenomenon that can be examined from multiple perspectives and at a range of spatial and temporal scales. From a perspective of daily ecosystem dynamics, even the most ordinary fire is a rare event. Working with rare events poses special challenges for statistical models, which are most useful in characterizing the behavior of many events, organisms, or forces, rather than individual ones.

A central question in statistical modeling of fire is therefore “how much should data be aggregated?” This plays out in both spatial and temporal dimensions. The answer is clearly dependent on the attributes of fire of most interest. For example, paleoecology fire activity is often quantified over decades or centuries from sediment charcoal records and no one would presume to identify either an individual fire or even the year of a fire (Whitlock et al., 2009). In contrast, observational fire records may track daily and even hourly fire progression precisely, though often retrospectively, such that the exact timing, the fire perimeter, and patterns of severity within the fire are known. An individual fire is just one event, however, and, therefore, only one realization of a stochastic process that is of limited use in estimating the attributes of future fires. An aggregate of individual fires is needed to develop the ability to forecast or project similar events. For example, statistical models of annual area burned (Flannigan et al., 2009, Littell et al., 2009) are a common parlance for characterizing regional fire activity, given a long enough temporal record (e.g., 30+ years) to be robust statistically.

Large Wildfires are Rare Events

VLFs are very rare events. We defined VLFa in the western contiguous US as those fires $\geq 50,000$ acres $\sim 20,234$ ha. By this definition, when fire activity was summarized by weeks, the Rocky Mountain Geographic Area Coordination Center (GACC) had only 3 weeks within which a VLF occurred out of 621 weeks available for analysis.

We can reduce problems associated with rarity by working at very coarse resolutions, e.g., years (annual area burned) or the conterminous USA, but analyses at these coarse scales are generally not useful for understanding the mechanisms driving VLF occurrence. For example, climatic factors correlated with the probability of a VLF occur in advance of the fire itself. Periods of high precipitation may lead to increased vegetation growth that becomes wildland fire fuel one or even many years into the future (Littell et al., 2009). Drought may lead to increased wildland fire probabilities weeks or months later. Wind and low humidity coincident with the fire will affect

the odds of that fire growing from a small fire to a VLF. If we move to finer spatial or temporal resolution, it becomes easier to untangle mechanisms, and predictions become more relevant. Issues with rarity offset the increased mechanistic understanding at these finer scales, limiting the feasibility of many standard statistical methods.

Imbalanced Observations of Fire versus No Fire

Logistic models are most robust with balanced data. For predicting the presence or absence of an observation (i.e., a VLF), equal numbers of 1's (presence) and 0's (absence) are ideal. Models with response variables that have more than an order of magnitude difference (e.g., ten zeros for every one) are especially fragile (He and Garcia, 2009). Rare events, such as VLFs, are typically unbalanced, and so we made compromises by extending the temporal window of megafire prediction (to weeks, see above) and the spatial domains to GACCs. The spatial resolution was later refined to a 60-km first using Level II ecoregions and then allowing for the spatial heterogeneity in predictors within an ecoregion. To maintain the concept of fires that are so large as to be currently rare events and also have enough observations to build reasonable models, we defined VLFs as 50,000 acres (20,234 ha), which was the largest size class for which we could build reasonable models. To understand the sensitivity of model selection and accuracy statistics to the presence of imbalanced data, we built an additional two models for each GACC using alternative definitions of megafire (4,407 ha and 10,117 ha).

Tradeoffs Across Spatial and Temporal Scales of Analysis

We considered a range of possibilities for structuring our analyses spatially. At the coarsest scale, we explored GACCs. There are 8 GACCs within the western conterminous USA. Within GACCs, we could also work at the scale of Predictive Service Areas (PSAs). There are approximately 100 PSAs within the western conterminous USA. The advantage of working at the GACC or PSA scale is that wildfire management and planning take place within these boundaries. The US Environmental Protection Agency (EPA) has also divided the USA into 15 "Level 1 Ecoregions" based on a framework developed by Omernik (1987). These are thought to be relatively homogeneous areas within which ecosystems (and the type, quality, and quantity of environmental resources) respond similarly to climate and disturbance (Bryce et al., 1999). Similarly, the conterminous USA has also been divided into 50 nested Level II ecoregions and 182 nested Level III ecoregions. These ecoregions form a second potential set of analysis scales, which divide the conterminous USA into ecosystems that might have similar climatic and vegetation drivers of wildland fire. In the end, we chose to model VLFs at the spatial scales of the GACCs and also on a 60-km grid.

The choice of temporal scale(s) for building models of VLFs is perhaps even more difficult, and involves four major challenges. First, although an intuitive way to classify time is the human calendar, seasonal climate does not adhere to it. For example, the beginning of the dry season in a particular region may be, on average, May 2nd, but in a given year, the beginning of the dry

season is unpredictable. Second, a fire season will not occur with annual regularity on the human calendar, and begins at different times in different ecoregions or other spatial delineations. Third, we are interested in predicting and understanding fire patterns at a fine temporal resolution, but this is precisely the resolution at which VLFs are rare events. Lastly, there are challenges with temporal congruence. Fires may begin before the recorded date of discovery, and climatic drivers of wildfire may occur years before a fire or even weeks after fires are initiated. For example, climate several weeks in advance of ignition could influence fire risk through reduced fuel moisture. Climate could also influence fire probability for days or even weeks after ignition via wind and lack of precipitation. Because daily resolution would have contributed to the imbalance in the data and is more subject to temporal autocorrelation, we aggregated the data by week and reduced each year to the core fire season. We included potential predictor variables summarized over several alternative time scales and lags, in order to identify the combination of predictor and timescale most highly correlated with the odds of VLFs.

APPENDIX D: STATISTICAL ANALYSIS OF MEGAFIRES AT THE REGIONAL SCALE

This appendix provides some additional notes on the statistical analysis. For more information, please see the full journal articles detailing this work :

- Stavros, E.N., J. Abatzoglou, D. McKenzie, and N. K. Larkin. 2014. Regional projections of the likelihood of very large wildland fires under a changing climate in the contiguous Western United States. *Climatic Change* 126:455-468.
- Stavros, E.N., J. Abatzoglou, N. K. Larkin, D. McKenzie, and E.A. Steel. 2014. Climate and very large wildfire fires in the contiguous western USA. *International Journal of Wildland Fire* 23:899-914.

We examined past associations between very large wildland fires (VLFs, 50,000 acres, or 20,234 ha) in the western contiguous USA and climate. Climate-based variables known to be prognostic for fire danger were used as predictors over several temporal windows before and after fire starts. We then considered how predicted seasonal changes in the climatic potential for VLFs would affect our estimated probability of VLFs across the same area.

We modeled past and future VLF probabilities across eight Geographic Area Coordination Centers (GACCs): Southern California (SCAL), Northern California (NCAL), Pacific Northwest (PNW), Northern Rockies (NROCK), Rocky Mountains (RM), Western Great Basin (WGB), Eastern Great Basin (EGB), and Southwest (SW). GACCs were defined by the U.S. National Interagency Fire Center (acquired 1 Oct 2011 from http://psgeodata.fs.fed.us/download.html/GACC_2009.zip).

Fire Data

For fire area, we used fire perimeters from the Monitoring Trends in Burn Severity (MTBS) dataset produced by the U.S. Forest Service (<http://www.mtbs.gov>, data acquired 1 Oct 2012). As used, MTBS spans 1984-2010 and includes area-burned and burn-severity data within nearly 6,000 individual large fire perimeters exceeding 405 ha across the western contiguous USA. Unburned islands (anything categorized as “unburned/unchanged” by MTBS) within the fire perimeter were not included in the burned area calculations to achieve a more accurate estimate of the total area burned (Kolden et al., 2012).

We used past records of fire discovery date to define the core fire season within each GACC.

The core fire season was defined as the time window within which fires accounting for the middle 95% of the area burned were within each GACC in an average year over the record. Fires with discovery dates outside of the core fire season were excluded from the analysis. We classified each week of the core fire season in which at least one megafire was discovered as a “megafire week,” weeks where at least one large fire was discovered but no megafires as a “large fire week,” and weeks in which no large fires occurred as a “no fire week.”

Climate Data and Derived Indices

Two gridded climate datasets were considered: (1) monthly temperature and precipitation from Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly et al., 2008), and (2) daily surface meteorological data from Abatzoglou (2013). Multiple fire danger indices were also available. Palmer Drought Severity Index (PDSI), a measure of soil moisture, is calculated from the monthly climate data while fire danger indices of the National Fire Danger Rating System (NFDRS) and the Canadian Forest Fire Danger Rating System (CFFDRS) are calculated from the daily surface meteorological data. NFDRS calculations used fuel model G (dense conifer stand with heavy litter accumulation) to maintain consistency with previous studies (Andrews et al., 2003) and used greenup dates defined by the first day of each year when the normalized growing season index exceeds 0.5 (Jolly et al., 2005; M. Jolly, personal communication).

We used six indices from the NFDRS and CFFDRS: (1) NFDRS 100-hour fuel moisture (FM100) represents the moisture content of dead fuels 1-3 inches in diameter or roughly the moisture content of $\frac{3}{4}$ -4 inches of soil. Lower values of FM100 represent dryer conditions; (2) NFDRS 1000-hour fuel moisture (FM1000) represents moisture content of dead fuels 3-6 inches in diameter. Lower values of FM1000 represent dryer conditions; (3) NFDRS energy release component (ERC) represents how hot a fire could burn and is directly related to the daily potential worst-case scenario, total available energy per unit area within the flaming front at the head of a fire. Higher values represent higher fire danger; (4) NFDRS burning index (BI) represents the potential difficulty of fire control as a function of spread rate and ERC. Higher values represent higher fire danger; (5) CFFDRS fine fuel moisture content (FFMC) represents the relative ease of ignition and flammability of litter and other fine fuels. Higher values represent dryer conditions; (6) CFFDRS duff moisture code (DMC) represents average moisture content of loosely compacted organic layers of moderate soil depth. Higher values represent dryer conditions.

Large Fire vs. Megafire Climatology

A composite analysis was used to answer the following question: do antecedent and concurrent fuel conditions and climate differ for megafires than for other large wildfires and for weeks during the fire season without large fires? Composite analysis includes lead-lag temporal composites of (1) weekly fire danger index percentiles over a 13-week period centered on the

discovery week, and (2) monthly temperature and PDSI for the year prior to and concurrent to the discovery week. Temperature and PDSI were used to examine fire climatologies up to a year prior to discovery and to provide insight to longer-term lagged effects of climate. The composite analysis staggers climate and fire danger index percentiles (to aid comparisons between GACCs) relative to the discovery week of fires (when x-axis is zero) within each GACC. Due to challenges in temporal overlap of individual fires and inconsistencies in the reported discovery date of each fire, the analysis is aggregated to the discovery week of each fire (weeks are defined by day-of-year, e.g., week 1 = January 1-7). The 95% confidence intervals of the composite means are estimated using bootstrapping (N=1000).

Probability of a Megafire Week

We estimated logistic regression models for each GACC to estimate the probability of a megafire week, i.e., a week when at least one megafire occurred within a fire season. Potential predictor variables included climate and fire danger indices as described above and in section 3. The hypothesized mechanisms relating each potential predictor variable to megafire probability suggest a variety of potential time lags. For example, climate several weeks in advance of ignition could influence fire risk through reduced fuel moisture. Climate after ignition could also influence fire probability via wind and lack of precipitation. To allow for these time lags during the model building, we used the composite graphs to identify predictor variables at multiple time lags. Note that PDSI and temperature (TEMP) are monthly indices that were assigned to all days of the month. Furthermore, explanatory variables used in this analysis are raw values rather than the percentiles applied by managers for fire-danger ratings. Percentiles are tied strictly to the model database used to generate them, thus using them over-calibrates models to the dataset used to generate them.

We applied the following model-selection procedure independently for each GACC. We built models by minimizing the Akaike Information Criterion (AIC), then removing insignificant ($p > 0.05$) variables one at a time by backward elimination. Next, we examined the resultant models for any correlated predictors (Pearson's correlation coefficient ≥ 0.8) or any predictors that were duplicated over time windows, retaining the earliest occurrence (e.g., if FFMC the week prior to discovery was used, no other FFMC variable from a later week was allowed). We confirmed that all predictor variables retained in the model still met the significance criteria ($p < 0.05$). Analysis of predictor influence on the probability of a megafire week used standard odds ratios.

We evaluated each model using a combination of precision, recall, and area under the receiver operating characteristic curve (AUC), which quantifies the trade-offs between true positives (TP; benefits) and false positives (FP; costs) (He and Garcia, 2009). An AUC of 0.5 indicates that the model predicts no better than random, whereas a value of 1.0 indicates that the model makes perfect predictions (Harrell, 2001). Precision is "a measure of exactness" returning the probability of correctly classifying a megafire while recall is "a measure of completeness" returning the probability of correctly classifying a megafire that is actually a megafire (He and Garcia, 2009). There is generally a trade-off between precision and recall. To calculate precision and recall, the model output—probability of a megafire week—was converted into binary

predictions of megafire week. We used a sliding classification criterion, in increments of 0.05, to translate model output into binary megafire predictions. For example, if one applies a classification criterion of $p \geq 0.5$, then any modeled predictions greater than or equal to 0.5 would be considered a prediction that a megafire would occur in that week. We evaluated model predictive accuracy across all thresholds, using AUC.

Megafire Future Projections

Climate data were used as predictors in VLF models defined per GACC, thereby projecting the probability that in a given week, a VLF will occur. The observed likelihood of VLF was compared to future projections using both time series of the proportional change in probabilities and Welch's t-tests. For each Representative Concentration Pathway (RCP) ensemble from 1950 to 2099 and for the observed ensemble 1979 to 2010, we used five-year moving averages, each divided by the mean of the observed record, to determine the proportional change in probability. Future proportional change projections for 2031-2060 were compared for individual General Circulation Models (GCMs) and the multi-model mean to the historical modeled (1950-2005) proportional change using Welch's pairwise t-test assuming unequal variances. We chose 2031-2060 to capture differences between a radiative forcing of 4.5 and 8.5 Wm^{-2} . Whereas the differences between RCP4.5 and RCP8.5 increase in the latter half of the 21st century, uncertainty associated with vegetation shifts and their feedback to fire climatology might change the climate-VLF associations used to build the models in this analysis. Nevertheless, time series were extended out to 2100 to capture the full potential difference qualitatively in probability of a VLF between RCP scenarios.

Two other analyses included (1) a plot of VLF seasonality and (2) the spatial distribution of the change in climate space from the observed record to the future. First, we examined seasonality by both plotting the probability of a VLF by week of year (y-axis) against each year from 1979 to 2010 (x-axis), and testing the difference, using Welch's t-test, in mean seasonal start week, end week, and season duration as defined by exceeding the threshold for classifying a megafire which was determined using the probability threshold where precision and recall intersect. (These thresholds are 0.225 in EGB, 0.125 in NCAL, 0.275 in NROCK, 0.175 in PNW, 0.200 in RM, 0.125 in SCAL, 0.125 in SW, 0.225 in WGB). Second, we examined the spatial distribution in the change of climate space by plotting the change in all calculated indices across the domain from the baseline conditions (1979-2010) to the more conservative future RCP4.5 scenario for 2031-2060. Regions where fewer than ten of the 14 models agree on the sign of change were excluded from the analysis. The change in frequency of extremes was examined using the percentage change in days or months (depending on the predictor variable) with extreme conditions. Extreme conditions are defined as exceeding the upper decile of the observed calculated index from 1979-2010 for ERC, BI, FFMC, DMC and Temperature. Because large fires have a proclivity for occurring during drought and low fuel moisture, the bottom decile was used for FM100, FM1000, and PDSI.

Summary Points

- We built statistical models at the scale of GACCs of the probability of a megafire, with climate-based variables, including fire-danger indices, as predictors.
- We estimated the probability of a “megafire week” with these models, as a compromise solution to achieve robust models of rare events (megafires).
- We projected these models onto future climate space, using RCPs 4.5 and 8.5 and an ensemble of global climate models.

APPENDIX E: MODELING OF HISTORICAL VLF AT SUB-ECOREGION SCALES: METHODS AND CONSIDERATIONS

The results of this work are summarized here. For more information please see the full journal articles detailing this work :

- Barbero R., J.T. Abatzoglou, E. A. Steel, N.K. Larkin. 2014. Modeling very large fire occurrences over the continental United States from weather and climate forcing. *Environmental Research Letters*, 9, doi:10.1088/1748-9326/9/12/124009

Relationships between very large-fires and climate factors were examined at weekly time scales and for Omernik level II ecoregions a 60-km spatial resolution. These ecoregions reflect climate and vegetation zones with common climate-fire responses and provide a suitable number of very large-fires required to build stable models. However, variability in climate and fire regimes persists within an ecoregion that is overlooked by aggregating all fires and climate information to coarse scales. To account for this, we model intra-ecoregion variability at tractable scales that reflect the spatial extent of the variability of top-down controls of fires, by spatially aggregating ecoregion to ~60-km resolution. Ecoregions that experienced fewer than 5 VLF were removed as were pixels where a majority of land cover was non-burnable defined by the presence of agriculture and barren land cover types.

The Monitoring Trends in Burn Severity (MTBS) database was used to obtain fire location, fire discovery date and burned area for large-fires over the contiguous U.S. from 1984-2010. Fires smaller than 404 ha were eliminated as was 'unburned to low' burned area for each fire as classified by MTBS. We define very large-fires (VLFs) as fires whose size exceeds the 90th percentile (5,073 ha) of MTBS fires greater than 404ha, resulting in a total of 927 fires across CONUS and 8343 large fires (LFs) that fell below VLF thresholds. Both VLFs and LFs were aggregated to ~60-km grid and 6-day time increment (hereafter we will use the term 'week' for simplicity) yielding a time series of 1647 weeks from 1984-2010 coded as 1 if at least one VLF was discovered within that week per voxel, and 0 otherwise. Modeling at the weekly timescale has the advantage of capturing intra-seasonal variability otherwise masked in longer timescales. However, this approach is not capable of capturing very short-term spread events.

We considered a set of predictor variables intended to capture different timescales of variability

through which the atmosphere can influence VLF occurrences from synoptic to sub-seasonal to interannual scales. We only selected the most relevant predictors to limit model complexity as outlined in Table E-1. We computed the 30-day Effective Precipitation (EP) index (Byun and Wilhite, 1999) that sums rainfall over the previous 30 days with a daily weight decreasing in a non-linear fashion from the last day of the period considered. We used the Palmer Drought Severity Index (PDSI) given its widespread usage in climate-fire studies, and PDSI averaged over the previous May-Sep, as it has been linked to changes in biomass availability in fuel-limited fire regimes. Four fire danger indices were also considered: Energy Release Component (ERC) and Burning Index (BI) from the National Fire Danger Rating System (Cohen and Deeming, 1985), Initial Spread Index (ISI) from the Canadian Forest Fire Danger Rating System (Van Wagner, 1987) and Fosberg Fire Weather Index (FFWI; Fosberg, 1978). Finally, to better account for vegetation distribution within ecoregions, annual climatologies of actual evapotranspiration (AET) and Climatic Water Deficit (CWD) were calculated following Dobrowski et al. (2013) as proxies of potential productivity and moisture stress. Also, previous studies (e.g., Balch et al., 2013) showed that fire activity was facilitated in the recent decades by the presence of invasive species such as cheatgrass (*Bromus Tectorum*) that invaded perennial shrublands in the cold deserts. As the seasonal timing of precipitation helps constrain the spatial distribution of cheatgrass extent (Bradley, 2009), we used the fraction of total annual precipitation in July-September as a proxy of cheatgrass locations. Note that these predictors are reasoned to model conditions conducive to VLF and not the exact location of VLF, since we did not include ignition sources.

Table E-1. Predictor variables and their source and frequency.

Very large-fire predictors	Data Source	Frequency
Relative humidity (RH)	Abatzoglou, 2013	Weekly
Fosberg Fire Weather Index (FFWI)	Abatzoglou, 2013	Weekly
Initial Spread Index (ISI)	Abatzoglou, 2013	Weekly
Temperature (T)	Abatzoglou, 2013	Weekly
Wind speed (W)	NARR	Weekly
Burning Index (BI)	Abatzoglou, 2013	Weekly
Energy Release Component (ERC)	Abatzoglou, 2013	Weekly
Effective Precipitation (EP)	Abatzoglou, 2013	Weekly
Palmer Drought Severity Index (PDSI)	PRISM	Monthly

PDSI during the previous growing season	PRISM	Annual
Actual Evapotranspiration (AET)	Dobrowski et al., 2013	Climate Normal
Climate Water Deficit (CWD)	Dobrowski et al., 2013	Climate Normal
Fraction of annual precipitation in Jul-Sep	PRISM	Climate Normal

We developed Generalized Linear Models (GLM) using a stepwise selection procedure in order to simulate VLF probabilities for each ecoregion. To do so, we considered all 60-km pixels within each ecoregion for the period of record in our modeling and treated them as independent samples despite the inherent spatial autocorrelation and serial correlation. The binomial predictand y (VLF occurrence vs Non-VLF occurrence) is defined such that $y=1$ if a VLF occurred during that week and $y=0$ otherwise (non-VLF week). This binary response is modeled as the probability (P) of VLF week via a logistic model with a logit link. While a model may be developed using all data and variables through a logistic model, numerous caveats arise that limit model robustness, particularly given the imbalance of VLF weeks to non-VLF weeks.

Resampling methods were used to assess model stability. Standard resampling protocols may be unfeasible as the rarity of VLF weeks in some ecoregions may yield samples with a complete absence of VLFs. Instead, we used all VLF weeks and resampled with replacement from non-VLF weeks drawn from the distribution of all voxels across time for each ecoregion. However, subsampling non-VLF weeks results in a bias in modelled probability. We corrected for this bias in VLF probabilities by including the fraction of non-VLF weeks randomly sampled compared to the number of non-VLF weeks in the population in the GLM.

Predictor variables that did not exhibit significant relationships were discarded from stepwise model selection procedure. Also, we did not allow interactive and non-linear terms in logistic equations. We used the Bayesian Information Criterion (BIC) to select predictors in the stepwise procedure that favors more parsimonious models. To select predictors in a robust fashion while limiting computation time and resources, we conducted 1000 Monte-Carlo simulations for each ecoregion using a subset sample of non-VLF weeks, yielding 1,000 different equations. We used the most frequent set of predictor variables from these simulations in subsequent modeling as we considered these to represent the most stable relationships.

Models were cross-validated and parameters estimated using a subset of observations that randomly resampled non-VLF plus all VLF weeks. We excluded 25% of non-VLF and VLF weeks for validation and used the remainder of the data to develop GLMs. We repeated this process 1,000 times and model performance was assessed by computing the Area Under the

Curve (AUC) between modeled probabilities and observations. The mean AUC across the 1,000 simulations was used to assess model skill, and the variability across the iterations to assess model robustness.

APPENDIX F:

PROJECTING MEGAFIRES INTO THE FUTURE

The results of this work are summarized here. For more information please see the full journal articles detailing this work :

- Barbero, R., Abatzoglou, J.T., Larkin, N.K., Kolden, C.A., and Stocks, B. 2015. Climate change presents increased potential for very large fires in the contiguous United States. *Int. J. Wildland Fire* DOI 10.1071/WF15083.

Prior studies have reported increased burned area for parts of the US by the mid-21st century with anthropogenic climate change; however, such studies have been limited to the western US and did not provide insights on future VLF occurrence. We extended prior work by Stavros *et al.* (see Appendix D) by resolving projected changes in VLF that account for varying climate–fire relationships facilitated through common vegetation assemblages at the ecoregion scale. Additionally, using the modeling framework detailed in section in Appendix E, we were able to capture intra-ecoregional variability in VLF at spatial (~60-km grid) and temporal (weekly) scales that may be more relevant for informing management approaches to climate change than coarser scale approaches. This empirical modeling effort cannot account for other factors that influence VLF such as changes in vegetation, land management and ignitions. However, by isolating projected changes in atmospheric drivers of VLFs, we sought to identify geographic hotspots of changing VLF occurrences. This guidance in turn may be useful in devising climate adaptation strategies for ecosystems and communities.

Climate projections were obtained from 17 global climate models (GCMs) using historical forcing experiments from 1971 to 2000 and Representative Concentration Pathways 8.5 (RCP8.5) forcing experiments from 2041 to 2070. We calculated a set of predictors with established links to VLFs (see Appendix E). Whereas all surface meteorological data were bias corrected through downscaling, a secondary bias correction was performed on all derived variables (e.g., fire danger indices, drought metrics). This bias correction forces data for the historical modeled period (1971–2000) to match the statistical moments of the observed distribution, and applies the same transformation to the future modeled period (2041–2070) thereby preserving differences between the two modeled datasets.

We projected VLF probability using downscaled GCM data at a 4-km horizontal resolution aggregated to the aforementioned spatiotemporal resolution and the GLM equations described in Appendix E. Specifically, we define VLF potential (P) as the expected number of VLFs per surface unit per week. We avoided extrapolating our model outside the observed range of data by limiting variables to the range of historical variability for each ecoregion. Projected changes in P were examined across 17 GCMs at weekly and annual time- scales between the mid-21st century (2041–2070) and late 20th century (1971–2000) runs. We focus on changes in the multi- model mean response (defined as the simple average of the 17 GCMs) and identify regions where the

signal is robust, defined by where the multi-model mean difference between mid-21st-century P and late-20th-century P exceeds two standard deviations of 20th-century runs (i.e. spread among models) and at least 90% of the models agree on the sign of change (IPCC, 2013). We also quantify changes in P for ecoregion across the 17 models to demonstrate the range and robustness of projected changes. Finally, we examined the length of the season during which atmospheric conditions are expected to be conducive to VLFs within each ecoregion. We defined the length of the VLF season as the number of weeks during which at least one pixel within an ecoregion had probability above the historical 99th percentile (defined at the ecoregion level).

Projected increases in P were modeled across much of the US, with the largest absolute increase in regions that observed numerous VLFs in recent decades including much of the inter-mountain West covering the Great Basin and Northern Rockies, as well as the Sierra Nevada and Klamath Mountains in Northern California. Increases were also projected across Northern Lakes and Forests, and in the Southern Coastal Plain, including much of Florida. These changes are consistent with increased temperatures, more frequent heat waves, and diminished soil moisture during the dry season. The largest relative changes in P were found across the northern tier of the US; however, these changes result in moderate absolute increases in P in regions that had historically low P.

Non-significant increases in annual P were projected in some non-forested ecoregions of the central US including the South-central semiarid prairies ecoregion. Respectively small and ambiguous changes in seasonal P were a function of muted and mixed changes in predictor variables historically important for VLFs in that region. Conversely, large increases in P were noted for the Western Cordillera ecoregion due to increased temperature, and decreased relative humidity and precipitation during the summer that collectively lower fuel moisture and increase fire danger indices in this flammability limited system. Consequently, a significant and nearly symmetric increase in the P on either side of the historic seasonal maximum was modeled for the ecoregion that results in heightened P during the core of the fire season and an extension of the seasonal window conducive to VLFs. An earlier onset of the VLF season is projected across the south-western US including the Warm deserts ecoregion, corresponding to overall warming and a northward retraction of the winter storm track that results in decreased spring precipitation and a resultant increase in the Initial Spread Index (ISI) – one of the leading predictor variables in that ecoregion. Conversely, models do not project any substantial change in these regions near the historical end of the VLF season. Similarly, models project an earlier onset of the VLF season in the Everglades in relation to anticipated warmer winter temperature and a return to normal conditions near the core of the historical VLF season.

Most ecoregions of the US not only experience higher mean annual P but also a temporal expansion of extreme probability with climate change. The largest seasonal expansion of extreme probability is projected for the Western Cordillera, Mixed Wood Shield, Cold Deserts or Southeast Coastal Plains ecoregions, where large increases in P are projected on either side of the seasonal maximum. However, most southern ecoregions (i.e. Everglades, Western Sierra Madre or Upper Gila Mountain) are likely to experience asymmetric changes in P, featuring an earlier onset of atmospheric conditions favorable to VLF development but only small changes near the historical end of the VLF season. Inter-model spread in projected changes in mean annual P and weeks of extreme probability are evident; however, nearly all model projections suggest increases above historical levels. One outlier model (GFDL-ESM2G) projects a decrease in VLF

for the Mixed Wood Shield arising from a reduction in climatic water deficit and its incorporation in modeling VLF for that region.

Summary points:

- Anthropogenic climate change is projected to increase VLF potential in the US through both an increase in frequency of conditions conducive to VLFs during the historical fire season and an extension of the seasonal window when fuels and weather support the spread of VLFs.
- The largest absolute changes are projected for regions across the western US where heightened VLF potential is the product of projected increases in fire danger and temperature, and decreased precipitation and relative humidity during the fire season.

APPENDIX G: LITERATURE REVIEW OF THE POTENTIAL FOR FUTURE FIRES AND VERY LARGE FIRES

In order to put our research in context, we examined how it fits with other studies predicting the potential for future fires and/or future very large fires.

Given the documented increase in wildfire size over the last several decades and the overwhelming evidence that suggests future climates will be warmer and drier in many regions throughout the continental United States, there is a growing body of scientific research predicting potential increases in fire frequency and fire size. We conducted a literature search to identify areas where this new line of research is predicting the occurrence of very large wildfires (VLFs) over the next 40 to 85 years (Figure G-1). Because of the large variability in how VLFs are defined, the spatial scales at which LFs and VLFs are predicted, the climate change projections used to identify future climate, and the temporal scale at which fires are predicted (weekly, monthly, fire season), we adopted a simplified map overlay approach to identify the areas where these recent studies predicted that future VLFs will occur.

We used internet search engines to identify 27 key publications that might provide long-term fire potential forecasts for further review (Tables G-1 and G-2). Each paper was reviewed to identify the fire potential forecast (fire size, fire occurrence, fire frequency, area burned) and whether specific repeatable forecast locations were provided (mapped forecasts at the pixel, ecosystem, ecoregion, or Geographic Area Coordinating Center [GACC]). Eighteen publications (Table G-2) did not meet the criteria for inclusion: either they did not provide forecasts of long-term fire potential or they did not provide spatially explicit information that could help identify areas where the study predicted increased or decreased future fire potential.

The remaining nine publications (Table G-1) suggest that fire potentials would increase under future warming scenarios. The majority of publications suggest an increase in fire occurrence and/or area burned estimated either monthly or annually but do not specifically forecast potential fire size. Three studies (Barbero et al., 2014b; Stavros et al., 2014c; Podschwit, in progress) provide specific forecasts of where LFs (>1000 acres) or VLFs (>12,355 acres – Barbero et al., 2014; >50,000 acres – Stavros et al., 2014c) are likely to occur.

The papers vary in the spatial and temporal scale at which they map future fire potentials. In Figure G-1, we mapped individual forecasts using the spatial scale described in the literature (that is, GACCs, ecoregions, and pixels). We show the areas where the greatest likelihood of more fire in the future was predicted by each study. Although the variables used to measure increased likelihood of future fire varied, the mapped areas tend to represent a >40% increase in probability of either more fire or of a future fire being categorized as a VLF.

For publications that used a gridded approach, we georeferenced the map figure and overlaid it with a 1/8-degree grid. When multiple temporal scales were reported, we mapped the forecasts at either the annual or decadal scale for ease of comparison.

Most studies focus on the western United States, with six out of nine publications focusing on the 11 western states (excluding Alaska and Hawaii). Two publications cover the continental United States, while one study focuses on the eastern United States. No study mapped in Figure G-1 forecast a high probability for increased likelihood of future fire across the entire west. When the results of the eight studies that included the western United States are combined, an increased fire potential is noted by at least one study for every land unit within the 11 western states. However, the combined results of these studies suggest a higher potential for increased fire probability, including VLFs, in the southwest, parts of California, the interior mountain west, and along the Rocky Mountains.

For the eastern United States, increased future fire potential was forecast throughout Appalachia, in the Ozark Mountains, and across the mid-western states of Wisconsin, Illinois, Indiana, and Ohio. Additional areas where fire potentials were forecast to increase included the Lake State Region (Minnesota and Michigan) and southern Florida.

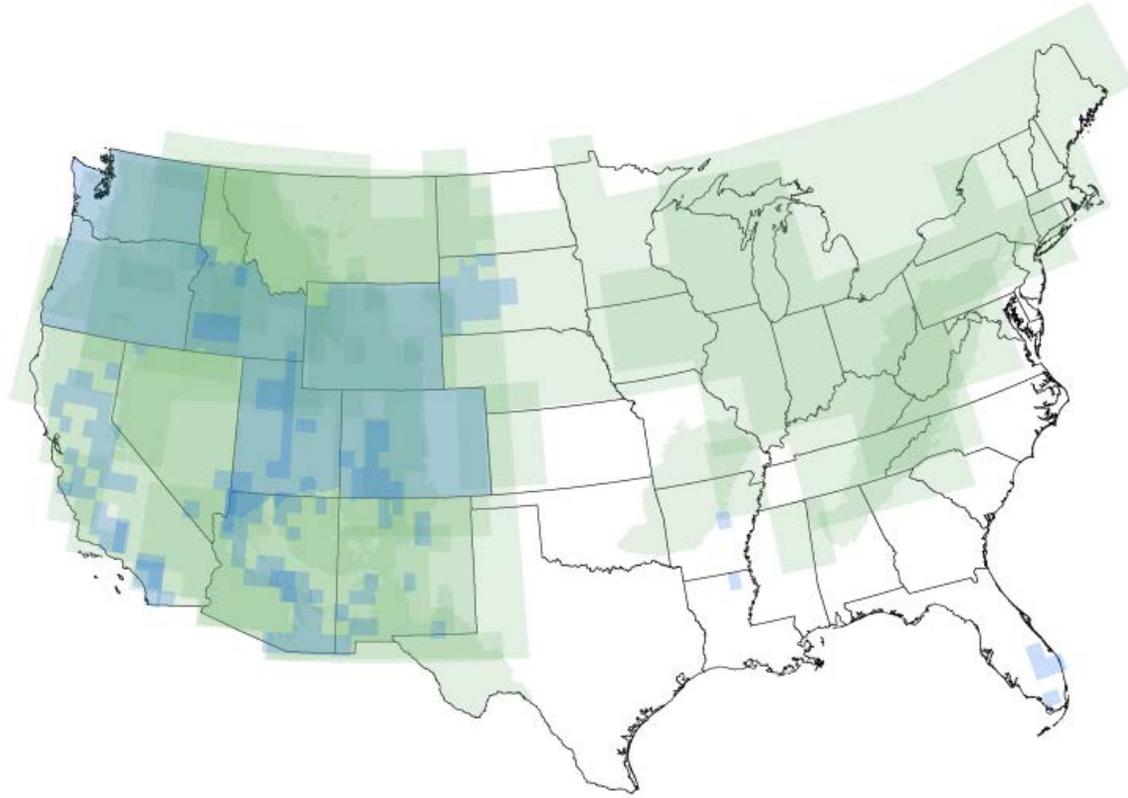


Figure G-1. Spatial area forecasts of increased fire potential (fire occurrence and area burned) and an elevated chance of VLFs. Nine studies (see Table G-1) indicated there would be more fire in the future (2040 to 2100) based on climate warming scenarios and downscaled General Circulation Models (GCMs). Three of these studies (Barbero et al., 2014b; Stavros et al., 2014b,c; Podschwit, in progress) provided forecasts of where increased probabilities of VLFs were identified (shown in blue). All other studies are shown in green. Darker shades indicate more studies forecasting increased fire potential.

Table G-1. Nine studies were identified that predict potential fire occurrence and provide specific, mappable locations for where fire potentials, including the likelihood of VLFs, are predicted to increase.

Publication	Future Fire Potential Prediction (Mapped in Figure 1)
Barbero et al. (2014b)	VLF (>12,355 acres) and large fire (>1,000 acre) probabilities for continental United States
Podschwit (in progress)	Large fires >1,000 acres across western United States
Stavros et al. (2014b,c)	VLF (>50,000 acres) and large fire (>1,000 acre) probabilities within western United States
Brown et al. (2004)	Potential increases in fire occurrence during 2010-2089 in the western United States
Guyette et al. (2014) (CGCM ^a)	Percent change in fire occurrence probability between 2001-2020 and 2080-2100 using PC2FM model in the continental United States
Guyette et al. (2014) (GFDL ^b)	Percent change in fire occurrence probability between 2001-2020 and 2080-2100 using PC2FM model
Hawbaker and Zhu (2012)	Annual fire ignition potentials and annual area burned statistics for 2041-2050 time period in the western United States
Hawbaker and Zhu (2014)	Annual fire ignition potentials and annual area burned statistics for 2041-2050 time period in the eastern United States
Spracklen et al. (2009)	Annual area burned in the western United States from 2046 to 2055
Yue et al. (2013)	Monthly annual area burned for 2046 to 2065 for the western United States

^a CGCM – Coupled General Circulation Model

^b GFDL – NOAA Geophysical Fluid Dynamics Laboratory Climate Model 2.1

Table G-2. Publications reviewed but not included in the map of expected increases in future large wildfires. These publications were not included because they do not include maps of future wildfire locations, do not include temporal timeframes when wildfire potentials are expected to increase, or do not specifically model future wildfire occurrence.

Publication	Region	Conclusions
Abatzoglou and Kolden (2011)	Southwest and Great Basin deserts	Suggested increased fire danger potentials and longer fire seasons
Abatzoglou and Kolden (2013)	Western United States	Found strong relationship between atmospheric conditions during current fire season and fire occurrence
Batllori et al. (2013)	Mediterranean, California	Climate-induced changes in fire occurrence
Barbero et al. (2014a)	Southeast United States	VLF occurrence related to long-term drought
Girardin and Udelsee (2008)	Canada	Fire occurrence across Canada expected to increase by 34% by 2061 to 2100
Hurteau et al. (2013)	Southwest United States	Implied that with future climate change, fires would be more frequent throughout the region
Hurteau et al. (2014)	California	Implied that future fires in California would be more frequent and emissions would be greater
Litschert et al. (2012)	Southern Rockies (Wyoming, Colorado, New Mexico)	Annual area burned predicted to increase across GCM models tested
Littell et al. (2009)	Western United States	Correlated wildfire occurrence to climate for historical record using historical and modeled climate data; no future wildfire forecasting presented
Liu et al. (2010)	Global	Used KBDI ^a to suggest that with increased global climate there would be a subsequent increase in wildfire occurrence and annual area burned
Liu et al. (2013)	Continental United States	Fire potential predicted to increase FEM using KBDI as a fire potential index

Liu et al. (2014)	Global	Burned areas globally expected to increase with increased climate warming, as much as 50% increase in west
Luo et al. (2013)	Southwestern United States	Increased potential for atmospheric conditions that favor large fire growth based on Hanes Index
McKenzie et al. (2014)	No spatial area	Smoke from wildfires in the future may be more intense and widespread
Mills et al. (2014)	Continental United States	Number and size of wildfires expected to increase across United States. Mitigating GHG emissions could lower the number and size (area burned) of future wildfires
Mitchell et al. (2014)	Southeast United States	High potential for increased fire occurrence throughout region
Preisler and Westerling (2006)	California	Produced statistical model to predict potential for large fire occurrence one month in future
Wimberly and Liu (2013)	Pacific Northwest	Expected increase in annual area burned throughout the region

^a KBDI – Keetch-Byram Drought Index

APPENDIX H: SMOKE EMISSIONS MAPS

We developed a map of gridded wildfire emission rates of particulate matter less than 2.5 microns in diameter ($PM_{2.5}$) for use in smoke impact potential calculations (Appendix I). Emissions data from a previous study were placed into the North American Regional Reanalysis (NARR) grid for the contiguous United States (CONUS). The $PM_{2.5}$ emissions data came from the Smoke and Emissions Model Intercomparison Project (SEMIP), funded by the Joint Fire Science Program (project #08-1-6-10). One of the SEMIP test cases examined the fuels, consumption, and emissions throughout CONUS (the Fire Everywhere test case). A set of sequential model runs of fuel loading, fuel consumption, and emissions were created for every 1-km grid cell in CONUS.

The selected $PM_{2.5}$ emissions data set from SEMIP was based on a 1-km fuelbed map and Consume 4.0. The 1-km fuelbed map is a crosswalk between the standard Fuel Characteristic Classification System (FCCS) fuelbeds and the Existing Vegetation Types map layer from the Landscape Fire and Resource Management Planning Tools Project (LANDFIRE). The FCCS-LANDFIRE fuelbeds include fuel loadings for downed woody fuels, shrubs, herbs, grasses, canopy fuels, snags, stumps, litter, lichens, moss, and duff.

Consume 4.0 is a model that estimates fuel consumption and emissions by fuel strata (Prichard et al., 2006). Climatologically representative fuel moisture values under dry conditions were used to predict the fuel consumption and emissions of a 100-acre fire for each fuelbed in the FCCS-LANDFIRE 1-km map.

These $PM_{2.5}$ emissions in tons/acre on the 1-km grid map from the SEMIP were overlaid with the NARR half-resolution grid used in this study (same grid and projection as the NARR, but at 64-km, double the grid spacing of the original NARR). In each grid cell, the $PM_{2.5}$ emissions of all the fuelbeds were averaged to generate the representative smoke emissions value for that grid cell. The 1-km pixels associated with the fuelbed that represented water (no fuel loading) were excluded from averaging. The resulting emission rate grid is shown in Figure H-1.

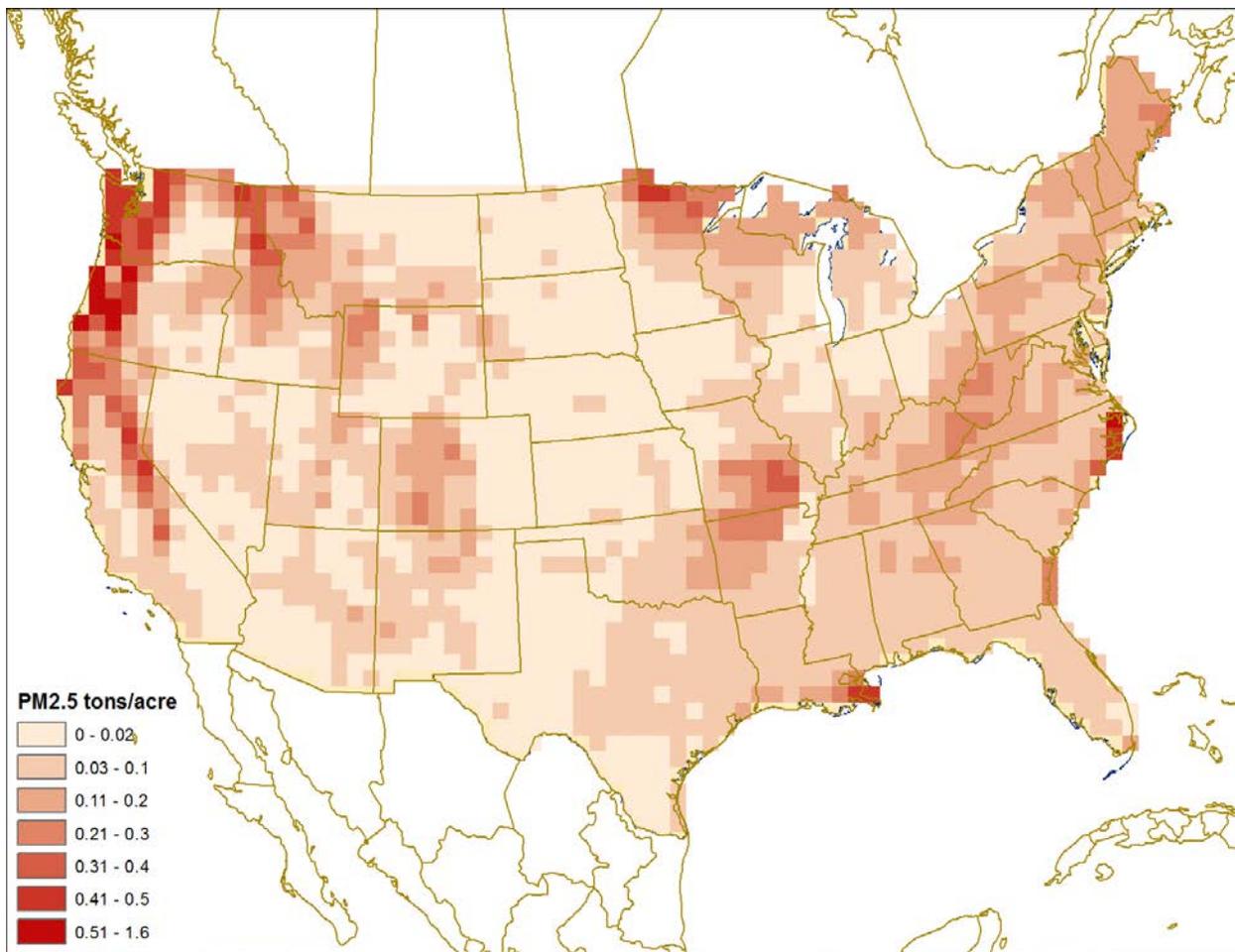


Figure H-1. Average $PM_{2.5}$ emissions in tons/acre for CONUS on the NARR half-resolution grid based on the FCCS-LANDFIRE 1-km fuelbed map and Consume 4.0 from the SEMIP Fire Everywhere test case.

For final processing of smoke impact potentials (see Appendix I), emission rates were classified into five equally spaced bins. The resulting binned emission rate map is shown in Figure H-2.

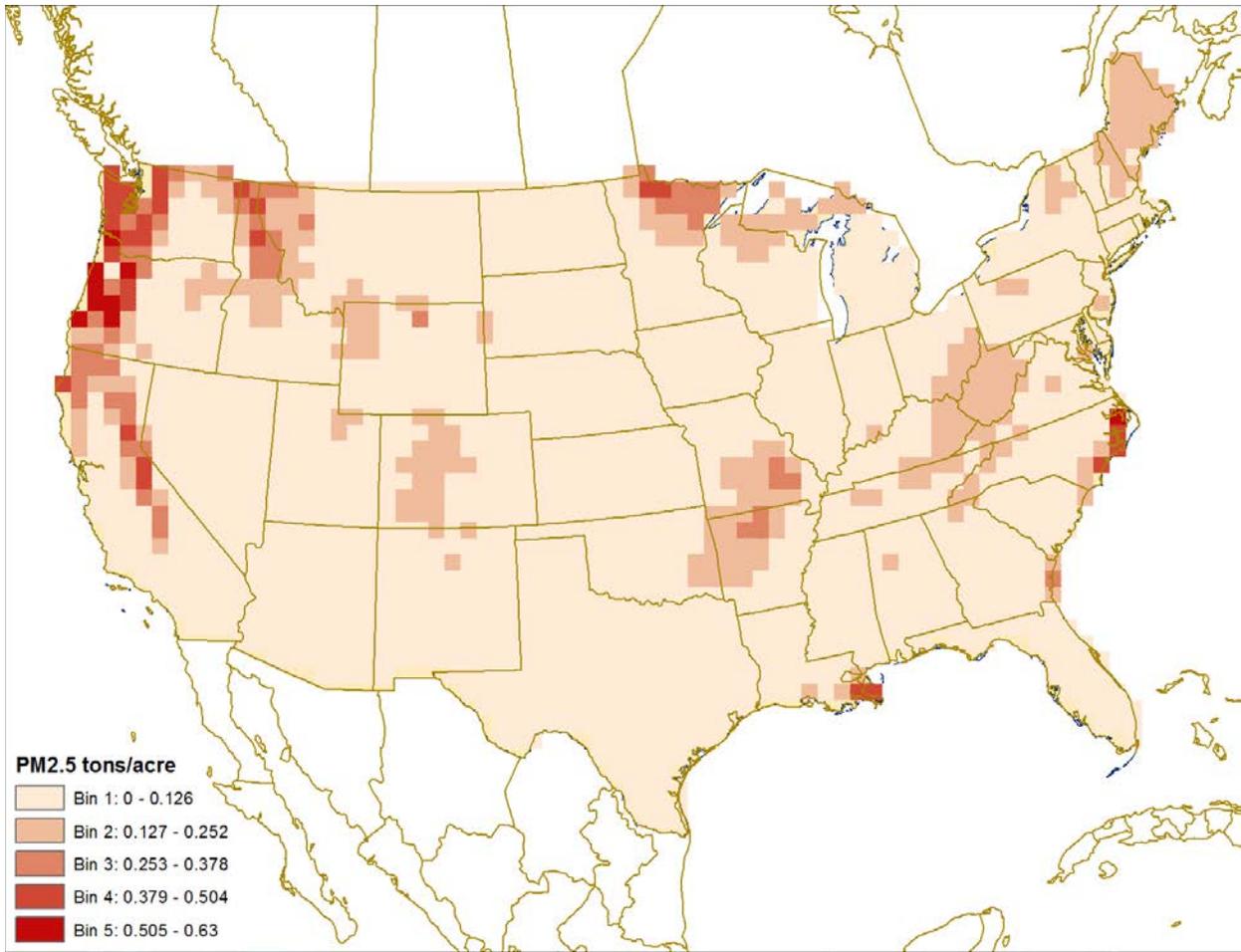


Figure H-2. Binned PM_{2.5} emission rates.

APPENDIX I: SMOKE TRANSFER FUNCTIONS

To determine the likelihood of smoke transport from a fire source location to all other points, we employed “transfer functions” using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Draxler and Hess, 1997, 1998). Given a starting point and gridded wind fields, HYSPLIT models the hour-by-hour path that a parcel of air takes as it moves through the atmosphere. Figure I-1 shows the source locations modeled as well as an illustrative example of a single HYSPLIT run originating in North Dakota.

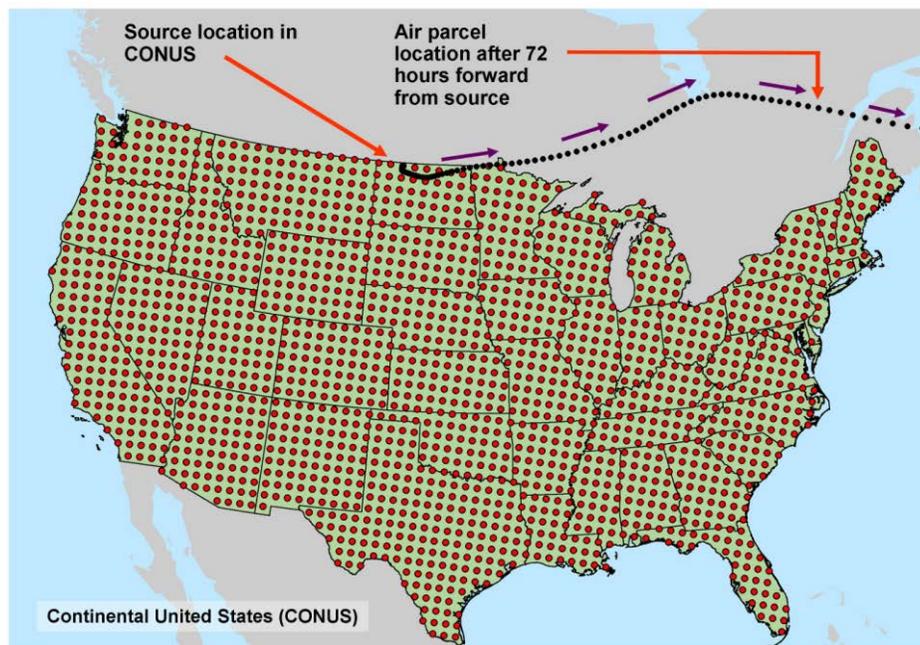


Figure I-1. Trajectory starting locations (red dots) and single trajectory example output (black dots).

The trajectory modeling was done as part of JFSP project # 10-S-02-1, which provides details on the trajectory modeling setup. This project used a subset of the trajectory results. For each of the starting locations shown in Figure I-1, we used 18 trajectories per day from January 1, 1979, through December 31, 2009. The 18 trajectories covered three starting heights (500 m, 1000 m, and 1500 m above ground level) at four starting times (0:00, 6:00, 12:00, and 18:00 GMT). Trajectories were followed forward in time for 120 hours (5 days). Wind fields were from the North American Regional Reanalysis (NARR).

Trajectories were converted to transfer functions for each site by combining all trajectories

within a single climatological week (e.g., January 1-7 across all years), counting hourly trajectory points within each analysis grid cell, and normalizing the resulting counts by the maximum count. Analysis grid cells were twice the size of the NARR grid (64 km²). Figure I-2 shows an example transfer function for southeastern Missouri in the first week of October. This shows the probability of transport from the origin to other locations in the domain. For example, 100% of the trajectories travelled through the origin cell in southeastern Missouri, and less than 5% of trajectories travelled through Ohio. For final analysis, weekly transport functions were combined to produce monthly results.

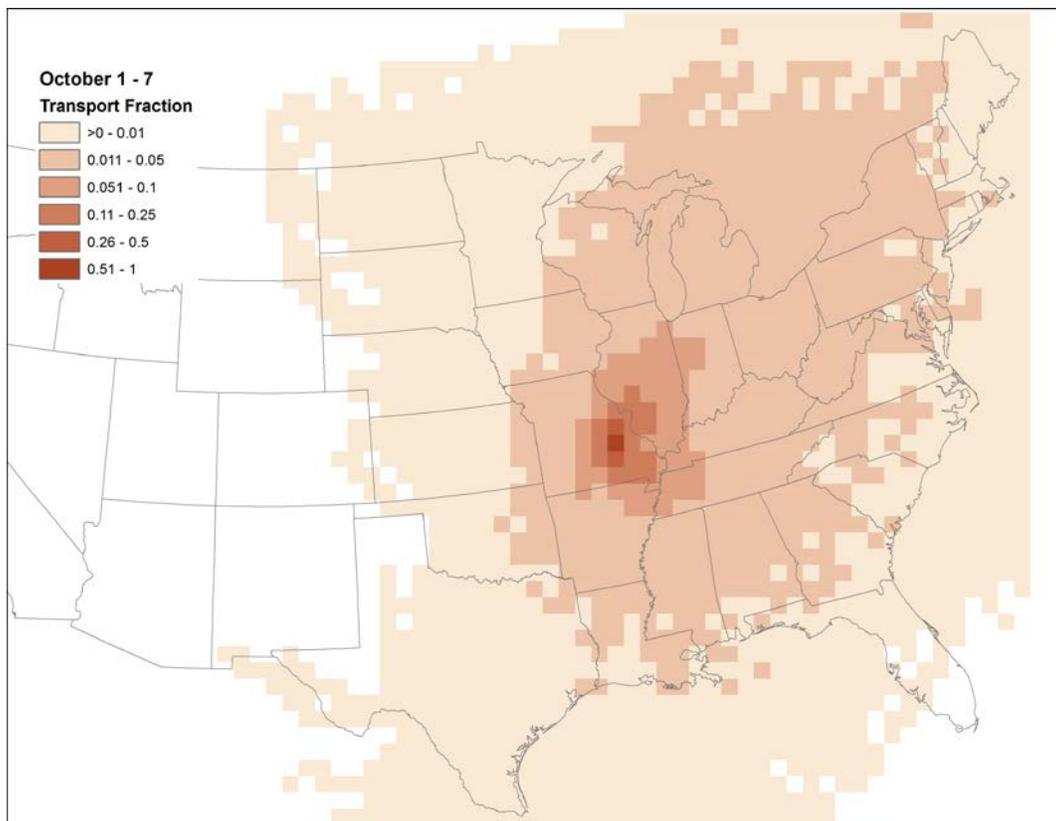


Figure I-2. Transfer function for the climatological week of October 1-7 for a grid cell in southeastern Missouri.

Transfer functions were intersected with a grid of population as part of the smoke impact calculation described in Appendix J. The population grid was developed from the 2010 U.S. Census numbers at the zip code level. Total zip code population was assigned to each NARR grid cell proportionally by area. Figure I-3 shows the gridded population map. Note that Mexico's and Canada's populations were not included in this analysis, so impacts are somewhat underestimated in locations with significant transport out of the United States, such as northern Minnesota.

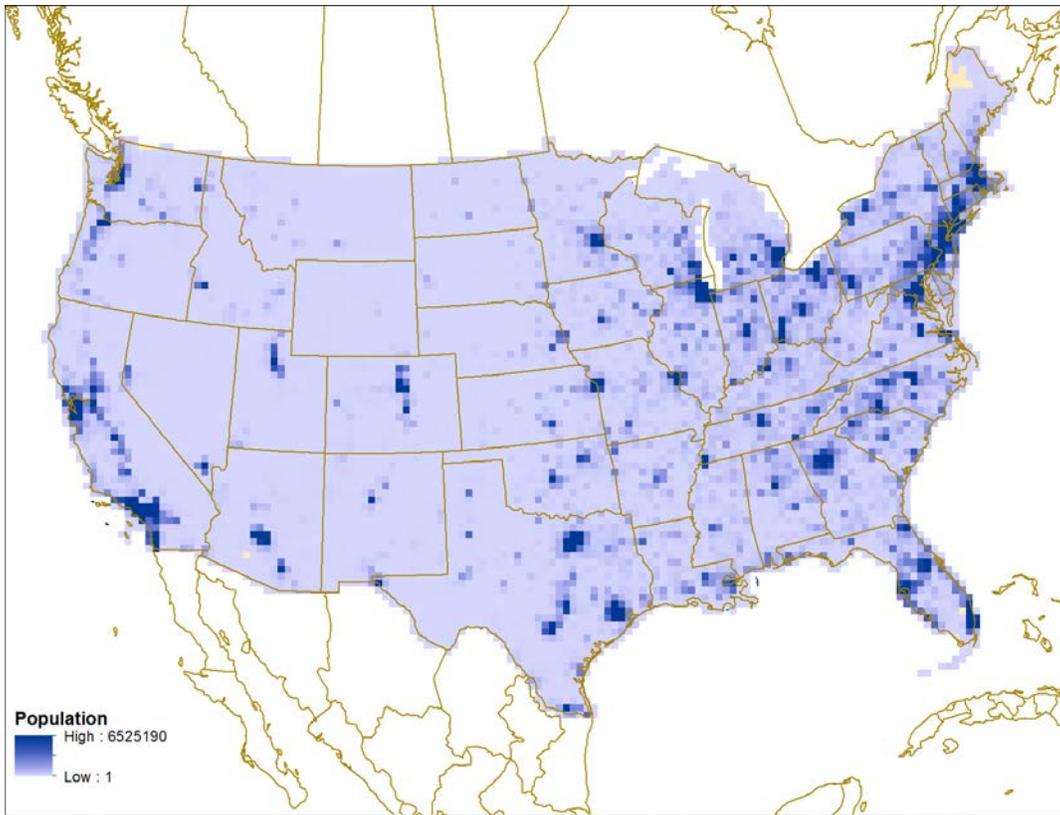


Figure I-3. Gridded population based on 2010 U.S. Census.

APPENDIX J: SMOKE IMPACTS USING TRANSFER FUNCTIONS

To assess the potential for smoke from a fire at a given location to impact populations, we created monthly smoke impact potential (SIP) scores by combining smoke emissions maps (Appendix H), with transfer functions and population (Appendix I). For a hypothetical fire at location l , the monthly transfer function estimates the likelihood of transport to each other location (ij) as a fraction less than one. The population at ij is multiplied by the transfer function value. This multiplication is done at all locations and the sum provides a metric of likely population impact for fires from location l on the given month. For example, as shown in Figure J-1 (left), smoke from fires originating near Point Reyes, California, in June is likely to transport to populated parts of California (Area 1). Conversely, in October (Figure J-1 right), the transport is more likely to be offshore (Area 2). This difference is subtle in the transfer function images, but the difference in total population impact across the domain is significant, as shown in Figure J-2.

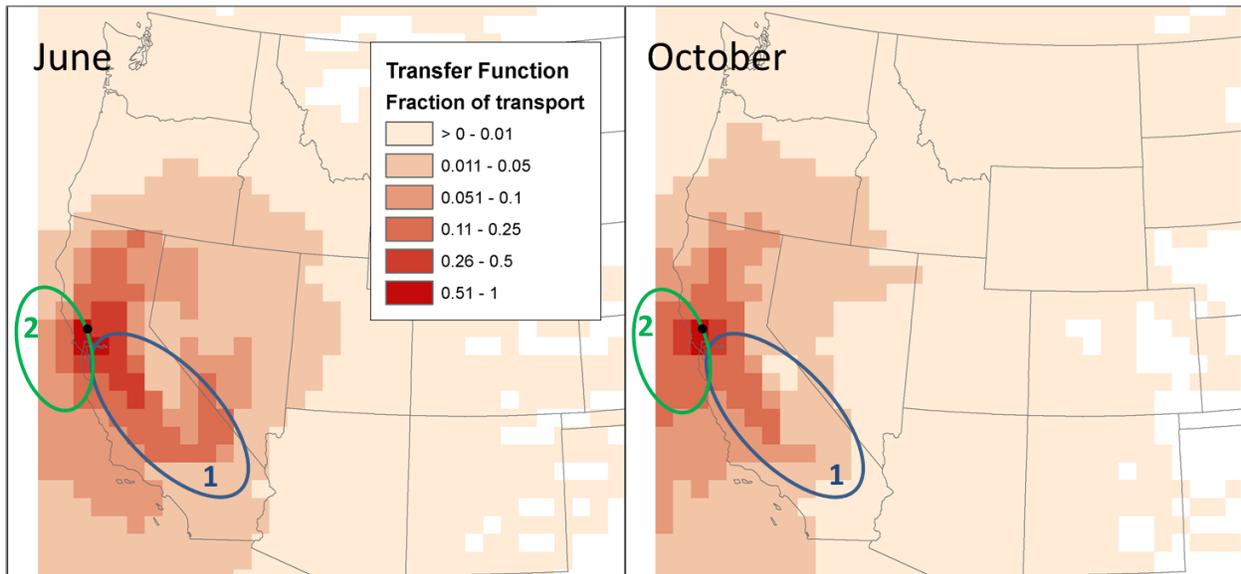


Figure J-1. Transfer functions for June (left) and October (right) for an origin near Point Reyes, California.

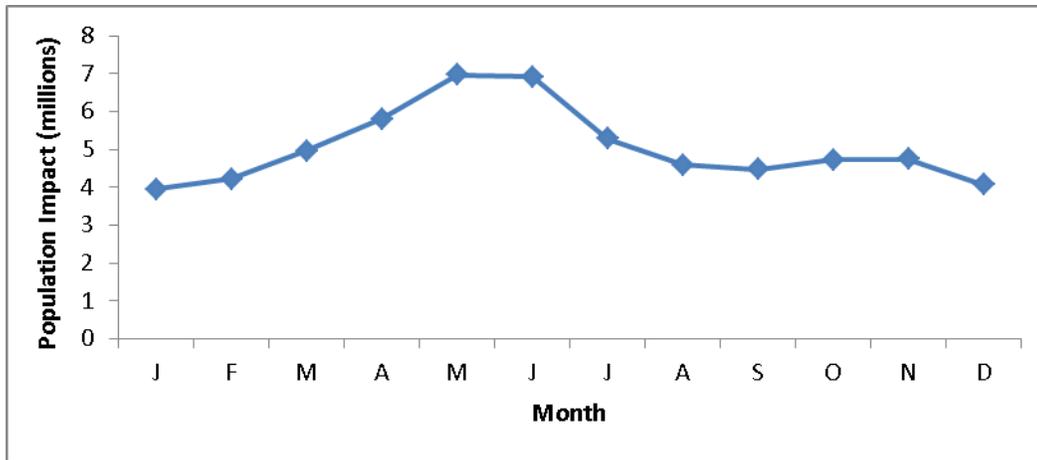


Figure J-2. Monthly population impact for smoke originating in Point Reyes, California.

The analysis above assumes that all fires produce similar smoke impacts. However, fires in some regions, such as heavily forested areas or regions with peat soils, emit more smoke per unit area burned than other regions, such as grasslands. To account for this, the population impacts were scaled by emission rates. Emission rates were determined as shown in Appendix H. Because emission rates vary by over an order of magnitude, and population health impacts are not expected to vary as much, we binned emission rates into five equally spaced bins. Thus, given the same transport population impact as calculated above, the location with the highest emission rate will have five times the emissions weighted impact as the location with the lowest emission rate.

Putting together the transport potential, population, and emission rate, we calculate the final smoke impact potential SIP_l at location l as

$$SIP_l = \sum_{ij} (t_{l,ij} \times p_{ij}) \times ER_l \quad \text{Equation J-1}$$

$t_{l,ij}$ is the normalized (1 at source cell, <1 elsewhere) transfer function value for source location l for grid cell ij

p_{ij} is the total population within grid cell ij , based on the 2010 zip code census

ER_l is the binned wildfire $PM_{2.5}$ emission rate for location l

The SIP is a qualitative index with non-physical units. For comparison with fire probabilities, we normalized SIP indices to the maximum value across all locations and months. Figure J-3 shows the SIP values for all months. SIP addresses two factors, the amount of smoke that would be generated by a hypothetical large fire, and the number of people that might be exposed to that smoke. SIP does not include the likelihood of a fire actually occurring. Thus, the areas with the highest SIP values are those with large emission potentials and large populations downwind. The spatial patterns are largely consistent from month to month.

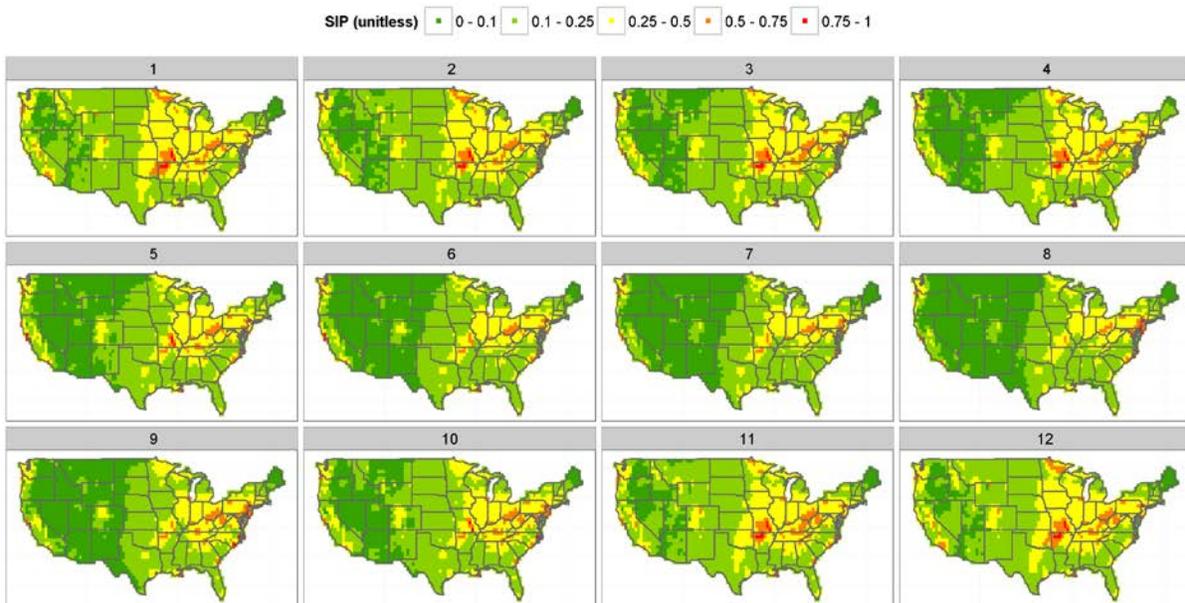


Figure J-3. SIP by month.

APPENDIX K: SMOKE CASE STUDIES

The BlueSky Framework (BlueSky, Larkin et al., 2009) and HYSPLIT Lagrangian dispersion model (Draxler and Hess, 1997, 1998) were executed in an ensemble modeling mode to develop probabilistic smoke impact analyses for eight hypothetical very large fire (VLF) scenarios shown in Table K-1. Results from two of these scenarios (shown in bold in Table K-1) are presented here as case studies. The VLF locations were selected from regions where the trajectory-based smoke impact analysis indicated the highest potential for human exposure to smoke from a future VLF.

The emissions and dispersion model simulations were conducted using the USFS BlueSky Framework version 3-5-1 (Larkin et al., 2009). Table K-2 summarizes the BlueSky modules used to develop emissions estimates and calculate smoke impacts for the VLF scenarios. Consume 4.0 is the Python recoding of Consume 3.0, completed by the Michigan Technical Research Institute, and the Fire Emissions Prediction Simulator (FEPS) plume rise module implements an adaptation of the Briggs plume rise algorithm.

For each VLF scenario in Table K-1, the smoke impacts from a 10,000-acre wildfire ignited at midnight local time were modeled each day from 1979 to 2008 during the month in which a VLF is most likely to occur (up to 930 HYSPLIT simulations per scenario). For the Ozarks case, a simulation was performed every third day during the three months in which a VLF in that region is most likely to occur. A VLF might burn 50,000 acres or more over the course of several days or weeks, but 10,000 acres is a reasonable burn area for the first day of a VLF event based on the behavior and spread of large fires that have occurred in the past. Each HYSPLIT simulation was run for 48 hours, with all of the fire emissions occurring within the first 24 hours. During the last 24 hours, fire emissions were turned off while smoke previously injected into the modeling system continued to be transported and dispersed. This approach simulates the potential smoke impacts over a 48-hour period from a 1-day burn cycle.

The HYSPLIT simulations were driven by three-dimensional meteorological data from the North American Regional Reanalysis (NARR) (Mesinger et al., 2006), a regional long-term, dynamically consistent, gridded weather and climate data set for North America at a 32-km horizontal resolution. The NARR combines a mesoscale numerical weather prediction model with advanced land surface physics and a data assimilation system that incorporates a full complement of observations, precipitation analyses, and satellite data to minimize model error.

Table K-1. VLF scenarios selected for probabilistic smoke impact analysis.

Scenario	Coordinates	Month Modeled	FCCS Fuel Bed
Southern Sierra	35.6° N 118.7°W	August	36 – Live oak – Blue oak woodland
Northern Minnesota	48.2° N 93.9°W	April	279 – Black Spruce – Northern white cedar – Larch forest
Northern Sierra	38.5° N 120.4°W	July	16 – Jeffrey pine – Ponderosa pine – Douglas fir – Black oak forest
Columbia River	46.0° N 122.7°W	August	305 – Red alder forest
North Carolina	35.7° N 76.2°W	April	170 – Pond pine – Little gallberry – Fetterbush shrubland
Salt Lake City	40.9° N 111.8°W	July	224 – Trembling aspen forest
West Texas	30.7° N 104.1°W	April	32 – Ponderosa pine – Pinyon pine – Juniper forest
New Jersey	39.7° N 74.6°W	July	107 – Pitch pine – Scrub oak forest
Ozarks	37.8° N 91.3°W	October-December	90 – White Oak – Northern red oak forest

Table K-2. *BlueSky modules used to develop emissions estimates and calculate smoke impacts for the VLF scenarios.*

Modeling Step	BlueSky Module
Fuel Loading	Fuel Characteristic Classification (FCCS) (McKenzie et al., 2007)
Fuel Consumption	Consume 4.0 (Prichard et al., 2006)
Emissions	FEPS (Anderson et al., 2004)
Time Profile	Western Regional Air Partnership (WRAP)
Plume Rise	FEPS
Dispersion	HYSPLIT Version 4.9 (Draxler and Hess, 1998)

HYSPLIT was configured to run full particle mode, rather than in full puff mode or a hybrid puff/particle mode. When a sufficient number of particles are modeled, particle simulations provide a more realistic representation of pollutant transport and dispersion. Lofted smoke emissions were released at the midpoint between the plume bottom and plume top values estimated by the FEPS plume rise module. Smoldering emissions, as well as the surface component of the flaming emissions, were released at 10 m above ground level (AGL).

HYSPLIT predicts pollutant concentrations on a user-defined unprojected latitude-longitude sampling grid. For each VLF scenario, a sampling grid at 0.2-degree resolution (approximately 20 km) was defined. The geographic area for each sampling grid was tailored for each scenario, but covered a region that would likely be impacted by smoke within 48 hours of a fire ignition. A typical sampling grid size was 20 degrees longitude by 20 degrees latitude. For this study, PM_{2.5} predictions from HYSPLIT represent a vertically averaged concentration between the ground and 50 m AGL.

Each HYSPLIT simulation in a VLF modeling scenario is identical except for the days of NARR data used. The result is an ensemble of hourly smoke impact predictions based on climatological transport patterns during the month(s) in which a VLF is most likely to occur. The ensemble model output is aggregated to develop a statistical analysis of the air quality impacts from smoke due to the VLF. The statistics developed for this analysis are defined in Table K-3. BlueSky performs this statistical post-processing and produces aggregated model results in Network Common Data Format (NetCDF) and Google Earth Keyhole Markup language (KML) format. Examples from the KML output are shown in the case studies. The raw hourly outputs from each simulation are preserved in NetCDF format for future analysis.

Table K-3. *Statistical metrics used in the ensemble modeling analysis.*

Statistical Metric	Definition
Average impact	The average PM _{2.5} concentration calculated from all hours of all HYSPLIT simulations in the ensemble.
Maximum impact	The maximum PM _{2.5} concentration calculated from all hours of all HYSPLIT simulations in the ensemble.
Probability of impact	The probability that a given PM _{2.5} impact level would be achieved, calculated as the percentage of HYSPLIT simulations in the ensemble in which a particular impact level was exceeded.

Northern Sierra

The Northern Sierra VLF is located in Amador County, California, at 4,500 feet in elevation approximately 40 miles southwest of Lake Tahoe. The predominant FCCS fuel classification in this region is Jeffrey pine, ponderosa pine, Douglas fir, and black oak forest.

Figure K-1 shows the maximum PM_{2.5} impact predicted for the Northern Sierra VLF case. This peak impact is the highest hourly near-surface PM_{2.5} concentration predicted by the HYSPLIT simulations in the ensemble, and represents the maximum short-term air quality impact that might be expected from a Northern Sierra VLF. The highest potential impacts are located in the foothills west of the VLF, likely a result of easterly nocturnal drainage flow out of the mountains and into the Sacramento Valley. These peak impacts affect numerous foothill communities, as well as larger cities such as Stockton and Sacramento. Significant peak impacts also extend down the east side of the San Joaquin Valley, impacting cities as far south as Fresno and Bakersfield. Finally, westerly flow conditions produce a potential for significant peak impacts in South Lake Tahoe and east of the Sierra in Reno and Carson City.

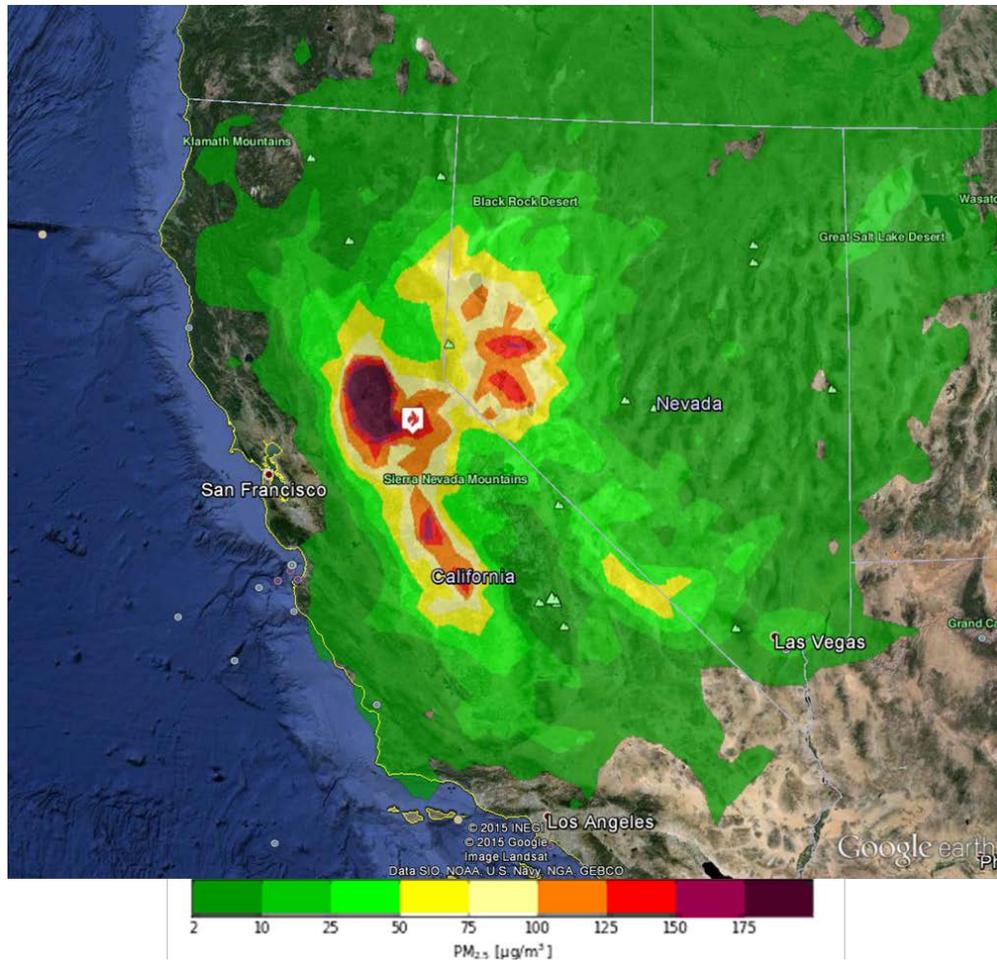


Figure K-1. Maximum predicted $PM_{2.5}$ concentration ($\mu\text{g}/\text{m}^3$) for a Northern Sierra VLF in July. The fire symbol indicates the VLF location.

Figure K-2 shows the probability that a VLF in the Northern Sierra in July would produce a measurable $PM_{2.5}$ impact. This probability is computed by calculating the percentage of HYSPLIT simulations in the ensemble in which the $PM_{2.5}$ concentration exceeded $1 \mu\text{g}/\text{m}^3$ for one or more hours. The highest probability of smoke impact occurs in the VLF burn area and in a lobe extending northeast over Lake Tahoe and into western Nevada. This is the result of westerly flow that is predominant in the region during July. A lobe of lower impact probability extends southward down the San Joaquin Valley. The effects of terrain blocking by the taller mountains southeast of the VLF are apparent.

One goal of the dispersion model case studies was to confirm that the transport patterns produced across CONUS using the simpler transfer functions (see Appendix I) were reasonable. Figure K-3 shows the transfer function for June for the same starting location as the full dispersion simulation in Figures K-1 and K-2. While the units and spatial resolutions of these figures are different, the gross spatial patterns are consistent, with the majority of impact shown to the northeast, with smaller impacts moving south.

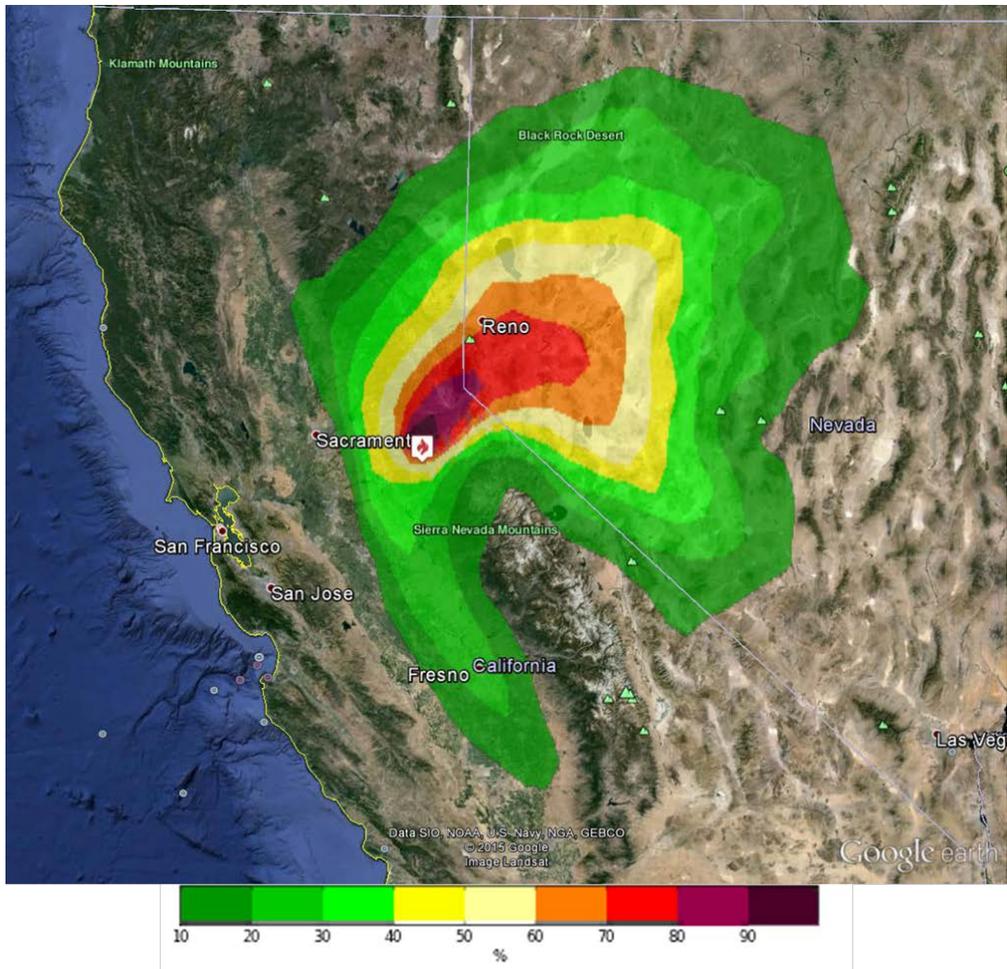


Figure K-2. Probability (%) of a $1 \mu\text{g}/\text{m}^3$ $\text{PM}_{2.5}$ impact from a Northern Sierra VLF in July.

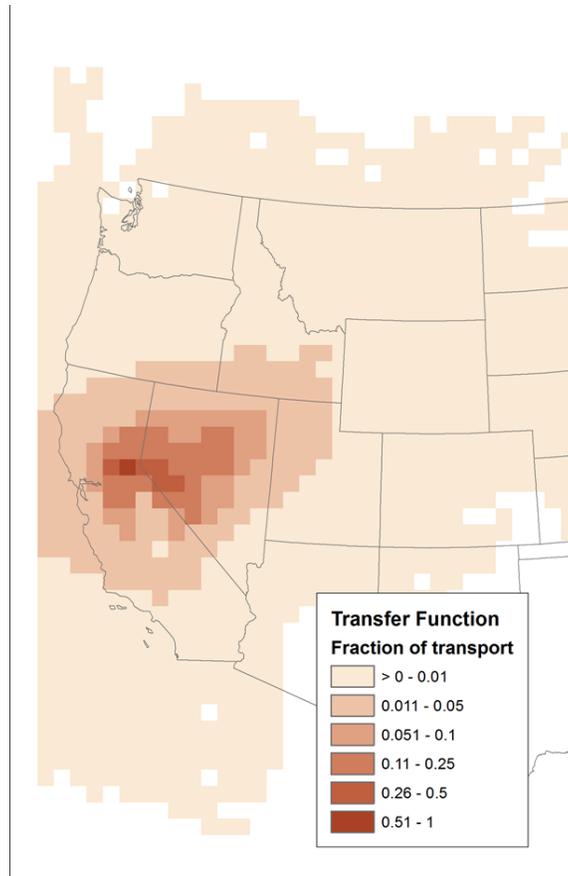


Figure K-3. Transfer function showing fraction of transport from fires originating in the Northern Sierra near Lake Tahoe in June.

Southern New Jersey

The southern New Jersey VLF is located in the New Jersey Pine Barrens in Burlington County, approximately 25 miles northwest of Atlantic City, 35 miles southeast of Philadelphia, and 75 miles southwest of New York City. The predominant FCCS fuel classification in this region is pitch pine and scrub oak forest.

Figure K-4 shows the maximum PM_{2.5} impact predicted for a VLF in the New Jersey Pine Barrens in July. The highest potential impacts are located in central and southern New Jersey, with significant peak impacts affecting several large cities, including Philadelphia and New York City. While peak impacts of greater than 50 µg/m³ are confined mostly to the Atlantic Coast region, smaller peak impacts from the Pine Barrens VLF extend throughout much of the northeastern United States.

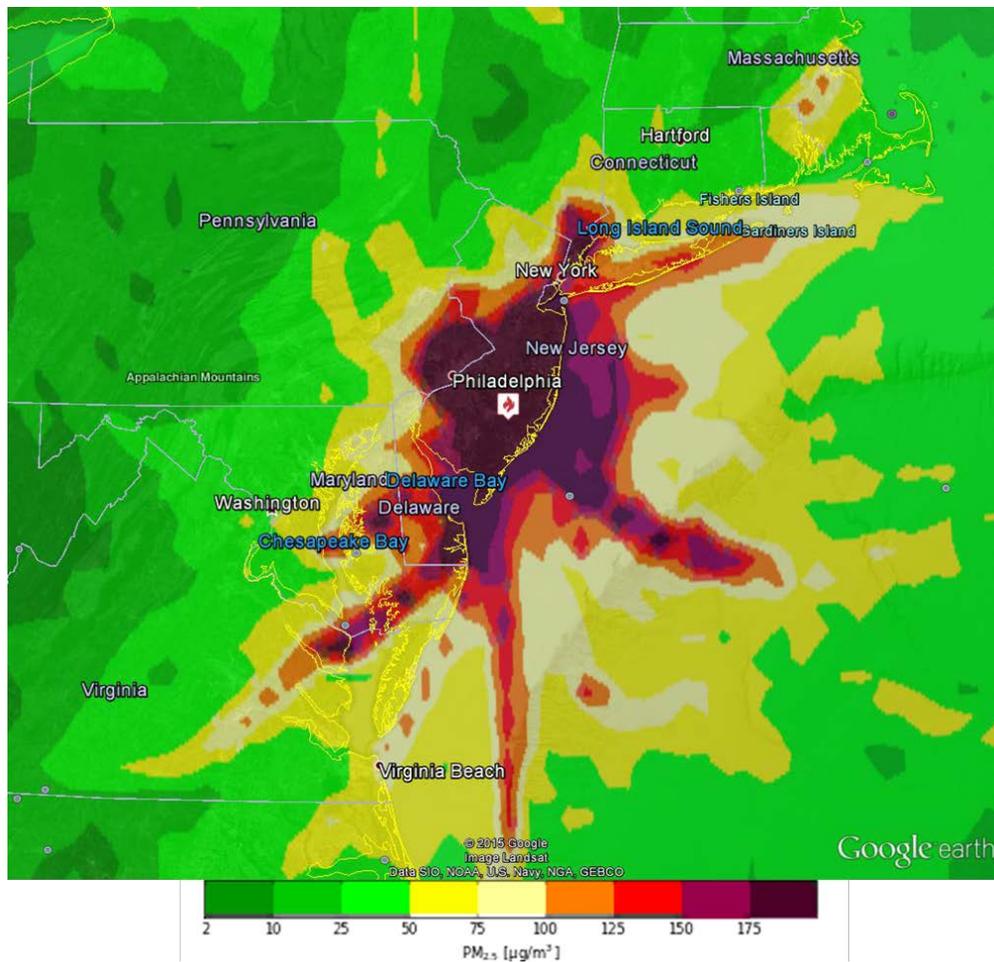


Figure K-4. Maximum predicted $PM_{2.5}$ concentration ($\mu\text{g}/\text{m}^3$) for a southern New Jersey VLF in July. The fire symbol indicates the VLF location.

Figure K-5 shows the probability that a VLF in the New Jersey Pine Barrens in July would produce a measurable (at least $1 \mu\text{g}/\text{m}^3$) $PM_{2.5}$ impact. The highest probability of smoke impact occurs in a lobe extending northeast from the VLF burn area, as a result of the climatological southwest flow in July. Smoke impact probabilities of greater than 40% occur from Atlantic City to New York City and Long Island, with impact probabilities of at least 10% extending further northeast into New England. **Figure K-6** shows the transfer function for the New Jersey Pine Barrens in July. While both the units and spatial resolution are different, the gross spatial patterns are consistent, with the majority of impact extending to the northeast. Cities that are generally upwind of the Pine Barrens, such as Philadelphia, have a relatively low probability of significant smoke impacts from a Pine Barrens VLF; however, the peak impact map (Figure K-4) suggests that these locations could experience significant smoke impacts if a VLF occurred during climatologically abnormal conditions (for example, southeasterly flow).

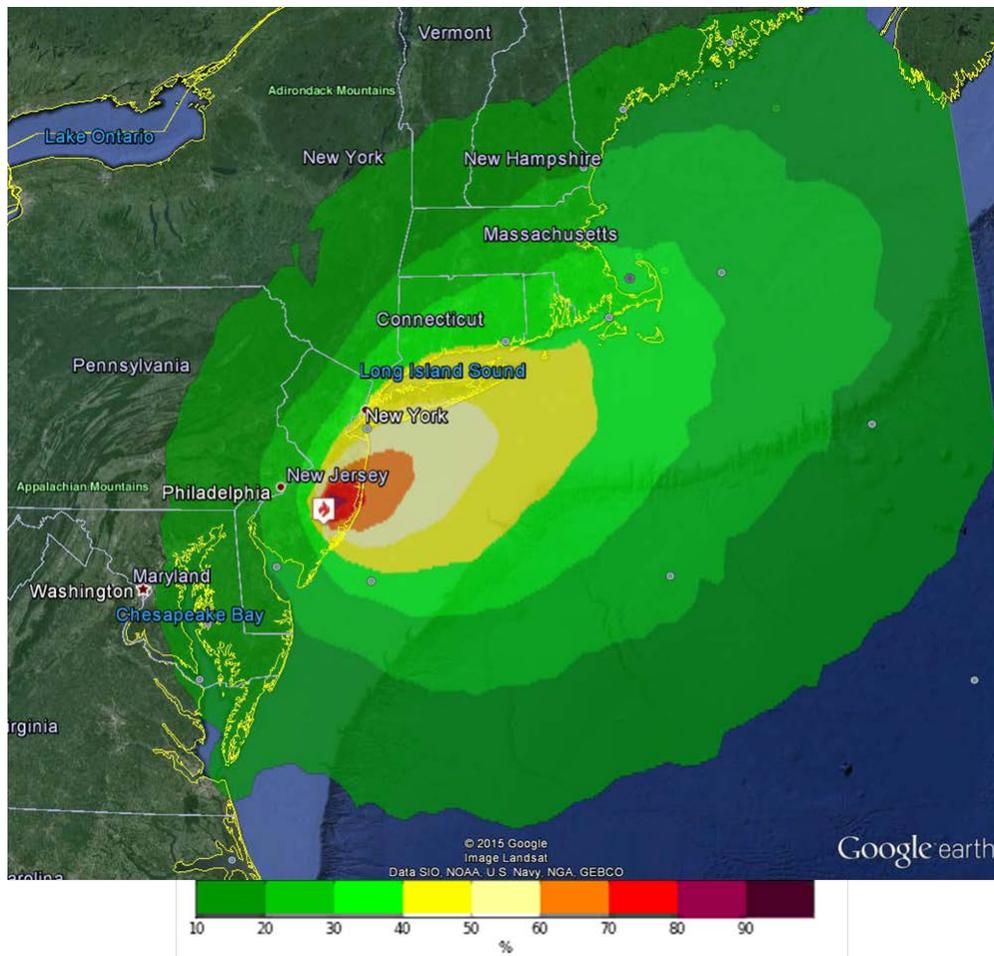


Figure K-5. Probability (%) of a $1 \mu\text{g}/\text{m}^3$ $\text{PM}_{2.5}$ impact from a New Jersey Pine Barrens VLF in July.

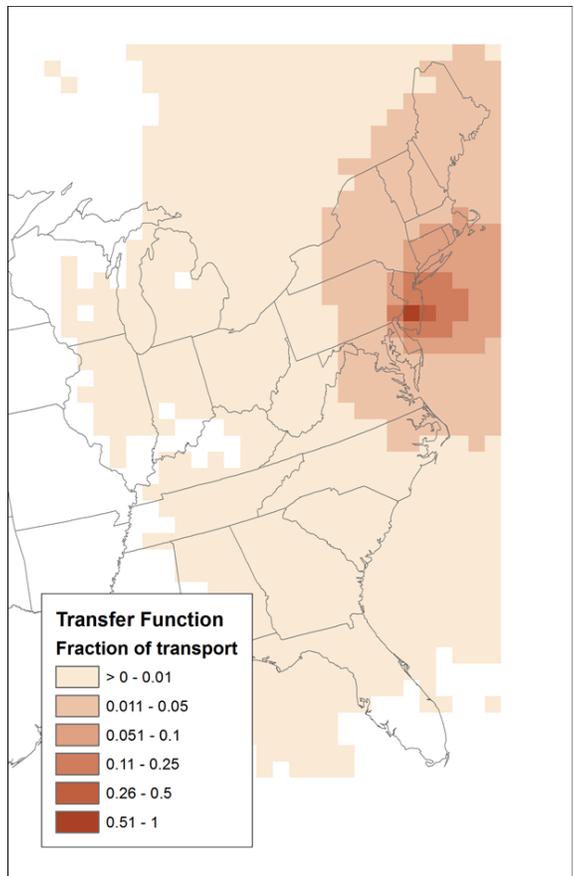


Figure K-6. *Transfer function showing fraction of transport from fires originating from the New Jersey Pine Barrens in July.*

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